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Editorial Preface

From the Desk of Managing Editor…

It may be difficult to imagine that almost half a century ago we used computers far less sophisticated than current home desktop computers to put a man on the moon. In that 50 year span, the field of computer science has exploded.

Computer science has opened new avenues for thought and experimentation. What began as a way to simplify the calculation process has given birth to technology once only imagined by the human mind. The ability to communicate and share ideas even though collaborators are half a world away and exploration of not just the stars above but the internal workings of the human genome are some of the ways that this field has moved at an exponential pace.

At the International Journal of Advanced Computer Science and Applications it is our mission to provide an outlet for quality research. We want to promote universal access and opportunities for the international scientific community to share and disseminate scientific and technical information.

We believe in spreading knowledge of computer science and its applications to all classes of audiences. That is why we deliver up-to-date, authoritative coverage and offer open access of all our articles. Our archives have served as a place to provoke philosophical, theoretical, and empirical ideas from some of the finest minds in the field.

We utilize the talents and experience of editor and reviewers working at Universities and Institutions from around the world. We would like to express our gratitude to all authors, whose research results have been published in our journal, as well as our referees for their in-depth evaluations. Our high standards are maintained through a double blind review process.

We hope that this edition of IJACSA inspires and entices you to submit your own contributions in upcoming issues. Thank you for sharing wisdom.

Thank you for Sharing Wisdom!

Kohei Arai
Editor-in-Chief
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Editorial Board

CONTENTS

Deep Neural Network-based Methods for Brain Image De-noising: A Short Comparison

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***Abstract*—Various types of noise may affect the visual quality of images during capturing and transmitting procedures. Finding a proper technique to remove the possible noise and improve both quantitative and qualitative results is always considered as one of the most important and challenging pre-processing tasks in image and signal processing. In this paper, we made a short comparison between two well-known approaches called thresholding neural network (TNN) and deep neural network (DNN) based methods for image de-noising. De-noising results of TNNs, Dn-CNNs, Flashlight CNN (FLCNN) and Diamond de-noising networks (DmDN) have been compared with each other. In this regard, several experiments have been performed in terms of Peak Signal to Noise Ratio (PSNR) to validate the performance analysis of various de-noising methods. The analysis indicates that DmDNs perform better than other learning-based algorithms for de-noising brain MR images. DmDN achieved a PSNR value of 29.85 dB, 30.74 dB, 29.15 dB, and 29.45 dB for de-noising MR image 1, MR image 2, MR image 3 and MR Image 4, respectively for a standard deviation of 15.**

Keywords—*CNN; Deep neural network; de-noising; MR image; PSNR*

I. Introduction

Noise is considered as unwanted signals causing imperfections and low resolution in image and signal processing, and may happen during the receiving and transmitting processes. Thus, further image analysis and processing may not be possible until we discard or reduce the noise in the images. In image de-noising, the main goal is enhancing the visual quality. Various methods are available in literature for removing the possible noise from images.

Donoho and Johnstone proposed adapting to unknown smoothness [1] and ideal spatial adaptation [2] using wavelet shrinkage for de-noising in 1994 and 1995, respectively. These techniques became the foundation for further gradient descent learning based methods. Zhang took one step forward in de-noising by proposing a learning-based method for improving the conventional approaches [3]. He developed a thresholding neural network using an improved and non-linear hard-soft threshold function. Sahraeian et al., proposed an improved TNN and cycle spinning for image de-noising [4]. Nasri and Nezamabadipour tried to improve Zhang's results by proposing another data driven function with three shape tuning parameters [5]. To enhance the results of TNN based methods, instead of using gradient descent algorithm, the authors in [6] proposed an optimized based technique.

Although the results were satisfactory, the researchers did not want to stop at this stage, and they wanted to go beyond the conventional gaussian denoisers. In this regard, convolutional neural networks are widely used in image processing due to their excellent performance for obtaining high quality output images. Jian and Seung developed a combined CNN with unsupervised learning for natural image de-noising [7]. Vincent et al. developed a new training principle for unsupervised learning and it became one of the basic deep learning techniques for noise removal aspects [8]. While using deep convolutional neural networks there is an issue in which we cannot train deeper networks easily. To address this problem, Mao et al. proposed symmetric skip connection combined with auto-encoders [9]. Zhang in [10] proposed a Dn-CNN method consisting of two main stages, residual learning and batch normalization. Deeper networks also cause gradient dispersion in which residual learning has been utilized in Dn-CNNs to tackle this issue [11]. There are also some other issues which deep neural network-based methods are suffering from. One is diminishing feature reuse, and the other is that increasing the number of parameters and layers does not have any advantage for them [12]. To address these issues Bin et al. developed a flashlight CNN method based on deep residual and inception networks that is able to hold many parameters [12]. Additionally, J. Zhang in [11] developed a diamond denoiser to deal with the issue of losing network's gradient caused by deeper networks.

A self-supervised based method for fluorescence image denoising has been proposed by Huang et al., [16]. In this approach, the authors utilized Wiener filtering and wavelet transformation, as two classic denoising techniques as well as DeepCAD to perform comparative experiments [16]. In another study conducted by Yang et al. [17], an efficient auto-encoder technique using convolutional neural networks to perform both classification and de-noising has been developed.

Content-noise complementary learning has been presented in [18] to denoise medical images. In this study to validate the performance of various de-noising methods, MR, CT, and PET images have been utilized. Structural priors based deep MRI super resolution has been developed in a study conducted by Cherukuri et al., [19]. Low rank structure and sharpness priors have been utilized in this study to enhance the visual quality of images. Convolutional de-noising autoencoders to discard noise from MR images has also been proposed in [20]. This technique provided better accuracy with less computation and data for de-noising the medical images.

In this paper we have a brief survey on several state-of-the-art de-noising approaches. We analyzed the results for MRI brain image de-noising. Thresholding neural networks, Dn-CNNs, Flashlight CNNs, and Diamond de-noising networks have been taken into account. The results indicate that deep neural network based methods have superior results compared to TNN based techniques. Among these deep neural network based approaches, Diamond de-noising networks (DmDN) perform well, followed closely by FLCNN, and DnCNN.

The rest of the paper is organized as follows: Section II is about CNN based image de-noising. A brief discussion about CNNs and how to perform CNN based de-noising has been provided. In Section III, we discuss image de-noising using thresholding neural network. In Section IV, we discuss several deep neural network methods. Section V is results and discussion. Finally, Section VI concludes the paper.

II. De-noising Using CNN

Sitting as a contrast from more traditional methods, convolutional neural networks can be used to great effect on de-noising images. CNNs have been the neural network of choice in the field of image processing due to their high effectiveness and can also be used when de-noising. These networks use their convolutional layers. There are multiple different methods regarding deep learning, but the ones that we discuss in this paper are feed-forward convolutional neural networks (DnCNN) and flashlight CNNs (FLCNN).

In order to de-noise an image, CNNs traditionally require a large training sample size, and learns by training with input-output pairs, images of noisy scans, followed by its clean variation. The network learns kernels through its convolutional layers, small weights that can detect patterns over the input image. The convolutional layers create a hierarchical representation of the input and can use this separation to learn to differentiate between the noise and the features of an image. Non-linear activation functions are then applied for complexity, and the network's outputs are compared to the actual clean image through a loss function, where it can adjust and try again. After much iteration, it then is tested on new images that have had Gaussian white noise added to them, tasking the CNN to de-noise the image [22].

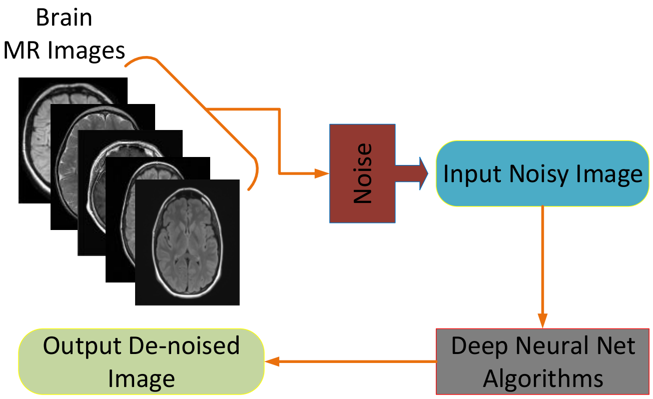

Fig. 1. The procedure of deep learning-based de-noising.

One of the methods we discuss however uses a deep feed-forward network, which can not only learn with overall smaller sample sizes but uses residual learning. It trains on images that already have noise and learns from it, working along with batch normalization in order to increase its accuracy [23]. In the case of the flashlight CNN, it uses a very similar strategy, while also using inception layers that help the network better handle Gaussian white noise. Fig. 1 shows the main procedure of de-noising using learning based approaches. Images have been obtained from [21].

III. TNN Based Methods

Standard hard and soft thresholding functions were first proposed in [3]. In this case, these functions became the basis and foundation of further thresholding based de-noising. Since the obtained results using these functions were not satisfactory, the researchers in the fields of image and signal processing attempted to enhance these methods and add more parameters to make them non-linear and differentiable to be used in a network called, “thresholding neural network’’. These functions which are the enhanced version of standard thresholds are called “improved thresholding functions’’ which were first introduced by Zhang [3]. The equations below indicate these improved soft and improved threshold functions:

$$L_{soft}(u,\tau) = u + \frac{1}{2}(\sqrt{(u-\tau)^2 + l} - \sqrt{(u+\tau)^2 - l}) \tag{1}$$

where, $L_{soft}(u,\tau)$ denotes the non-linear soft threshold, u is the WT components, τ is the threshold value and $l > 0$ is a function parameter (user defined) [3].

$$L_{hard}(u,\tau) = \left(\frac{1}{1+\exp\left\{\frac{-u+\tau}{\psi}\right\}} - \frac{1}{1+\exp\left\{\frac{-u-\tau}{\psi}\right\}} + 1\right)u \tag{2}$$

where, $L_{hard}(u,\tau)$ denotes the non-linear hard threshold, u is the WT coefficients, τ is the threshold value and $\psi > 0$ is a fixed function parameter (user defined) [3].

Although these functions have been used in various studies for image denoising, the results have not been quite satisfactory and there is some space for improvement. Thus, another nonlinear and differential threshold function has been presented by Sahraeian [4] as shown by Eq. (3). This function has been inspired by Zhang’s improved hard threshold function.

$$L_S(u,\tau) = \begin{cases} m(e^{n|u|} - 1).\mathrm{sgn}(u) \quad , & |u| \le \tau \\ (|u| + he^{-n|u|}).\mathrm{sgn}(u), & |u| > \tau \end{cases} \tag{3}$$

where, $L_S(u,\tau)$ is the Sahraeian’s nonlinear threshold, n controls the function’s shape and refers to the thresholding effect’s degree. Additionally, parameters m and h are used to preserve the continuity and derivative at τ [4].

The researchers did not want to stop here, and they moved forward to present a function with more flexibility and capability. Thereafter, Nasri and Nezamabadi-pour [5] presented other nonlinear functions with three shape tuning parameters which are formulated.

$$\Gamma(u,\tau,i,j,g)=\begin{cases} u - 0.5\dfrac{\tau^{i}\times g}{u^{i-1}}+(g-1)\tau \quad , & |u|>\tau \\ 0.5\dfrac{g\times|u|^{j}}{\tau^{j-1}}\operatorname{sgn}(u) \quad , & |u|\le\tau \\ u+0.5\dfrac{(-\tau)^{i}\times g}{u^{i-1}}-(g-1)\tau \ , & |u|<-\tau \end{cases} \tag{4}$$

where, τ is the threshold value, u denotes the WT coefficient, i and j controls the function's shape, and g calculate the asymptote of the function [5]. For further details and information about the structure of TNN and WT based de-noising, please refer to [3].

IV. Deep Learning Based Methods

A. *DnCNN*

Nowadays, due to the availability of large-scale datasets and progress in deep learning algorithms, CNN approaches attract lots of attention in imaging technologies [10]. The construction of feed-forward convolutional neural networks (DnCNNs) for de-noising has become the basis for de-noising using deep learning [10]. In this structure, to improve the computational time and also to enhance the quality of the de-noised image, batch normalization and residual learning have been utilized, leading to this approach becoming one of the more efficient and effective gaussian denoisers. Conventional deep NNs can estimate a clean image directly, but DnCNNs can remove and discard the clean image by adapting it to the residual learning strategy [10]. Training a single DnCNN as a blind gaussian denoiser gives better results compared to alternative methods. As mentioned earlier, residual learning and batch normalization are used in this structure. Residual learning has been utilized for solving performance degradation issues [14].

The developed DnCNN utilizes only one residual unit for predicting the residual image [10]. If we compare residual mapping with the original unreferenced mapping in terms of learning, residual mapping is easier, so deep CNN models can be trained easily [14] [10]. On the other hand, although training based on stochastic gradient descent (SGD) is effective and simple, internal covariance shifts can largely reduce the training efficiency [15] [10]. So, alleviating the covariance shift is also a challenging task in deep CNN models and is the reason that batch normalization is used in these networks [15] [10]. The combination of residual learning and batch normalization provides us with stable training, fast training procedure (because of using batch normalization), better qualitative and quantitative results [10]. The main structure of the DnCNN model is depicted in Fig. 2.

As can be seen, the network's input is a noisy image corrupted by gaussian noise. Here, instead of learning a mapping function, we can proceed by adapting residual learning for training the residual mapping [10]. Additionally, in the proposed network with depth *D*, there are three types of layers [10]:

- Conv+ReLU is used for the first layer with 64 filters with the size 3×3×c. Note that *c* is the channels' number. Also, ReLU has been utilized to give nonlinearity.
- Conv+BN+ReLU is used from layer 2-D-1 with 64 filters of size 3×3×64. Batch normalization (BN) has also been used in these layers.
- Conv is utilized in the very last layer with c filter of size 3×3×64 for reconstructing the output image.

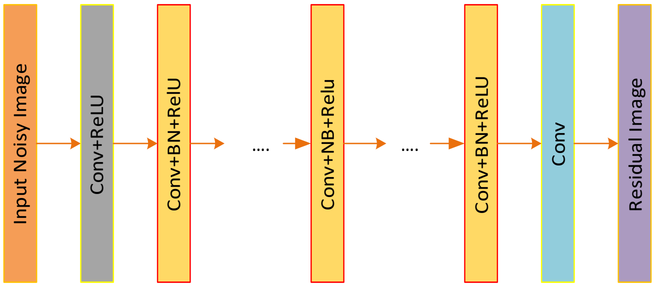

Fig. 2. The structure of DnCNN [10].

B. *Flashlight CNN (FLCNN)*

Flashlight CNNs are another type of convolutional neural network implementing deep NN for noise removal processes. The main structure of this method is based on the combination of deep residual and inception networks [12]. Utilizing inception layers provides us with overcoming and addressing the reuse of diminishing features while tackling additive white gaussian noise. As shown in Fig. 3, this network consists of two main phases [12]:

- Warmup phase which utilizes convolutional layers (typical or conventional CNN). There are two main stages in this phase. The first one employs 3×3 kernels with 64 features and the second one employs 5×5 kernels with 64 features.
- Boost phase utilizes wider inception layers (residual) leading to growth and increment in the number of networks' parameters while overcoming the reducing feature reuse.

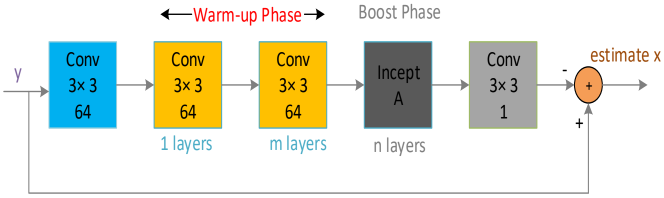

Fig. 3. The architecture of FLCNN with noisy input of *y* and estimate *x* [12].

C. *Diamond De-noising Network (DmDN)*

Images' detail and important characteristics and information may be diminished by doing excessive scaling [11]. Although the convolutional network is deeper, it may be easy to lose the gradient of the network. To address these issues, Diamond Shaped (DS) multi-scale feature extraction has been utilized in this network to extract the information of the images' features [11]. This fixed scale-based network is called a Diamond De-noising network (DmDN) [11]. This network contains three main parts as below [11]:

- Feature extraction of input noisy images.
- Feature extraction of multi scales.
- Clean image reconstruction or output image.

V. Results and Discussions

In this part, we have performed two experiments to validate the efficiency of various de-noising methods. Note that the images have been contaminated by additive white gaussian noise (AWGN) with zero mean and different standard deviations. For TNNs we used "sym4" with one decomposition layer. The training parameters are available in [11] and are the same as the original works used in this study. Axial DWI brain imaging obtained from [13] is used in the experimental part. We have used four single images at various moments of the original data (see Fig. 4). The de-noising results in terms of PSNR values for various standard deviations are shown in Table I. As neatly shown, DmDNs perform better than other de-noising approaches as it achieved the highest PSNR values. The results indicate that deep learning-based techniques outperform TNN models for de-noising MR Images.

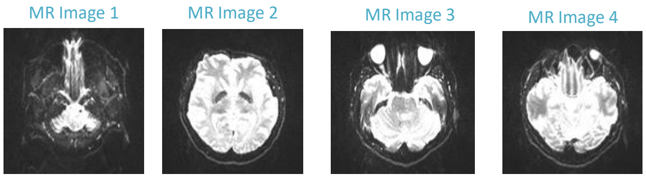

Fig. 4. Four test single images [13].

TABLE I. Denoising Comparison of Various Learning Approaches in Terms of PSNR Values (dB)

MR Images	**sigma**	**TNN-Zhang**	**TNN-Nasri**	**Dn-CNN**	**FLCNN**	**DmDN**
MR Image 1	15	24.02	24.23	29.72	29.83	**29.85**
	25	21.98	22.14	27.23	27.36	**27.47**
	50	19.45	19.54	24.25	**24.47**	24.46
MR Image 2	15	24.65	25.16	30.61	30.72	**30.74**
	25	22.75	23.11	28.42	28.59	**28.62**
	50	19.86	20.10	25.44	25.61	**25.64**
MR Image 3	15	23.78	24.10	29.01	29.11	**29.15**
	25	21.83	22.05	26.84	27.01	**27.06**
	50	19.53	19.78	24.03	24.24	**24.29**
MR Image 4	15	24.01	24.31	29.33	29.41	**29.45**
	25	21.45	22.14	27.01	27.14	**27.17**
	50	19.20	19.84	23.84	24.02	**24.09**

In the next experiment we utilized another data set obtained from Kaggle [21] to compare the performance of various deep neural net based approaches quantitatively. Some of these images are depicted in Fig. 5. In this experiment, as can be seen from Fig. 6, we compared DmDn, FLCNN, DnCNN, TNN-Nasri and TNN-Zhang over several standard deviations. The results indicate that the first three deep learning methods perform well in de-noising brain MR images. Among the first three neural net approaches, DmDn outperforms the others. Although these methods perform well in de-noising MR Images, they may not work perfectly for other types of datasets such as hyper-spectral remote sensing and standard test images or even if we apply other types of noise and perturbations.

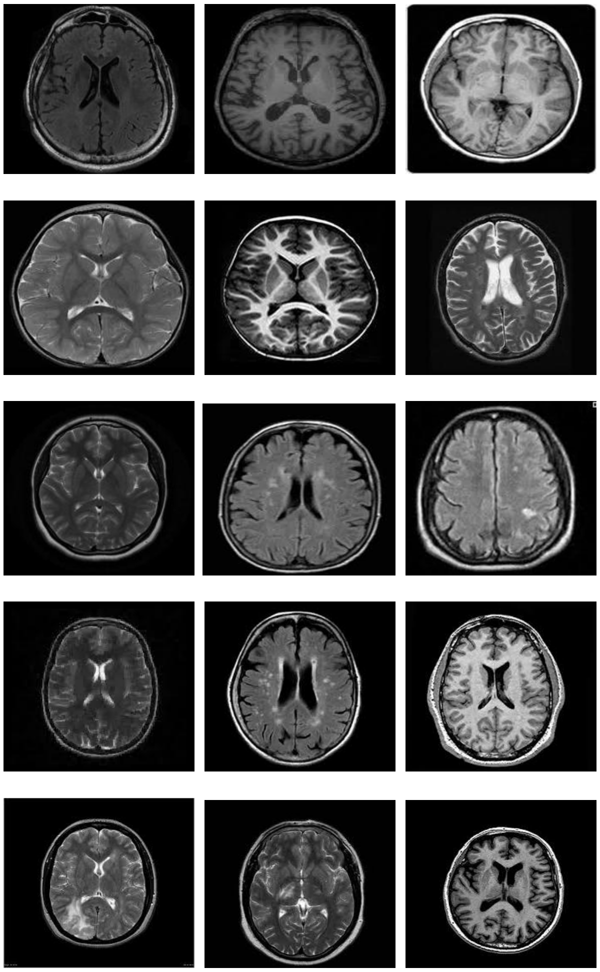

Fig. 5. Some of the brain MR images used in the experimental part [21].

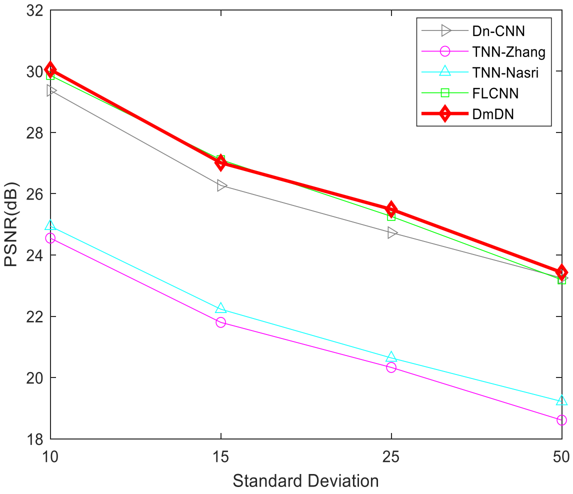

Fig. 6. Comparison of performance analysis of various learning algorithms for different standard deviations.

VI. CONCLUSION

Images may be influenced by many types of noise, leading to a decrease in their visual quality. Trying to find a suitable de-noising method for discarding this noise has always been categorized as a challenging task for researchers in the fields of signal and image analysis. This work provides a survey and comparison between several learning based de-noising methods such as TNNs, Dn-CNNs, Flashlight CNNs (FLCNN) and Diamond de-noising networks (DmDN) in terms of PSNR values. The quantitative results indicate that DmDN can be a promising method for brain MRI de-noising as it achieved the highest PSNR values for de-noising MR images 1-4 for a standard deviation of 15. In this study we have used AWGN, and we realized that increasing noise level decreases PSNR values. For future work, we will analyze the performance of some state-of-the-art methods in the presence of various types of noise.

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Assessing and Mitigating Network Vulnerabilities in Philips Hue and Nest Protect Smart Home Devices

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Abstract*—The Internet of Things (IoT) has gained momentum across various sectors, particularly in the consumer market with the adoption of smart devices. IoT extends internet connectivity to physical devices, enabling control via smartphones, environmental sensing, and updates. However, smart home devices are susceptible to cyberattacks due to vulnerabilities, lack of monitoring, and built-in security. They can also participate in botnets, leading to large-scale attacks. Vulnerabilities in these devices may exist at the sensing, network, or application layers, impacting data confidentiality, integrity, and service availability. This research aims to identify network-layer vulnerabilities affecting the 'Availability' of Philips Hue and Nest Protect. By establishing a test environment, the baseline behavior of these devices is examined, followed by scans for open ports and services to detect network-based threats. Volumetric flood attacks are then conducted to assess susceptibility, and findings are shared to define the devices' default security posture. The research also addresses security issues related to home routers and aims to reduce the attack surface of smart home devices through isolation and network-level protection. This involves deploying a Firewall to isolate smart devices from non-IoT devices and prevent intrusions.

***Keywords*—Internet of Things (IoT); Smart Home Devices (SHDs); network vulnerability assessment; Philips Hue; Nest Protect**

I. INTRODUCTION

The Internet of Things (IoT) has been an important technological revolution that has enabled the emerging Industry 4.0 [1]. By extending the capabilities of physical devices used in our daily life to the Internet, IoT, with the use of standard Internet Protocols, has allowed communication between humans and things [2], [3]. Smart devices are context-aware, perform autonomous computing, and connect using wired or wireless mediums [4]. Since these devices carry out only a limited set of tasks, they have low hardware specifications [5]. Some smart devices require intermediate nodes to communicate on the internet. Owing to these reservations, smart devices use lightweight communication methods and lack complex built-in security schemes [6].

In a smart home, internet connectivity is extended to consumer appliances [7] such that human–device communication can occur seamlessly. For example, the Philips Hue smart lights can be controlled using a smartphone, and the Nest Protect alerts the user whenever smoke is detected [8], [9]. Smart Home Devices (SHDs) have gained immense popularity and have become an important part of modern living. In 2019, an estimated 8.6 billion devices were connected worldwide [10] and this number is expected to increase to 29.4 billion by 2030. The worldwide unit shipments of SHDs for 2021 were nearly 900 million [11], [12], [13]. While one set of statistics shows how popular SHDs are becoming, another set of statistics questions how secure these devices are. In 2022, the worldwide annual number of IoT-related cyberattacks amounted to 112 million [14].

Security is a vital requirement for all communication systems. Numerous security solutions that have evolved have focussed only on traditional computing. SHDs are the least secure of internet hosts [15] and both their widespread growth and heterogeneity have opened new and significant attack surfaces [16], [17]. Hence, the security of IoT devices is more critical than that of traditional computing devices [2], [18]. As in [19] cautioned, a compromise in SHD security not only affects the digital world but can also have serious implications in the physical world, causing harm to people.

In an enterprise, the complex task of monitoring and managing both IoT and non-IoT devices is handled by automated solutions and dedicated technical staff. In contrast, the security responsibility of a smart home falls on the user. Unfortunately, many consumers lack awareness about the potential risks these connected devices can cause and fail to implement adequate security measures [20]. Furthermore, many manufacturers of consumer network devices may not find an incentive to release frequent updates and patch vulnerabilities [21]. These gaps form the primary motivation to conduct this research and find out whether the devices we use have vulnerabilities. Hence, this research aims to secure two SHDs – the Philips Hue Smart Lighting and the Nest Protect Alarm.

The commonly prevalent security issues are highlighted by foundations such as the OWASP [22] and recommendations are provided by institutions such as the UK Government, ENISA, and the ETSI [23], [24], [25]. However, owing to inexperience in Cybersecurity and lack of security-focussed development, manufacturers still flood the market with insecure devices. For example, the DDoS attack against Dyn, in 2016, was conducted using compromised consumer IoT devices. This suggests that vulnerabilities in a SHD, when not addressed, can turn it into digital weapon [26].

Davis et al. [27] categorize SHD vulnerabilities as Physical, Network, Software, and Encryption. While software and encryption related vulnerabilities are more manufacturer-centric, this research focuses on the network-level vulnerabilities. It is a cause for great concern that SHDs lack security standards and that vulnerabilities get exposed only during usage. It is imperative to perform vulnerability assessments of SHDs and identify network insecurities. Two studies have assessed the security posture of both the Philips Hue and the Nest Protect and have provided security ratings [20], [28]. Both Copos et al. [29] and Yadav et al. [30] have conducted a traffic analysis of the Nest Protect. The first objective of this research is to setup a test network to assess the network insecurities in the Philips Hue and the Nest Protect. Based on the vulnerabilities identified, attacks are launched against the devices and the responses are recorded. This forms the second objective of this research.

A typical Smart Home follows a flat network architecture – both IoT and non-IoT devices are on the same subnet served by a home Gateway. It is highly possible that such a coexistence may open new avenues for cyberattacks [31]. In addition, the home Gateway is the most compromised device and its services may increase the attack surface [15]. Hence, this research also discusses vulnerabilities in the home Gateway and how those could increase the risk factor.

Generally, devices in a traditional network are secured using three approaches namely: 1) device-level protection, 2) isolation, and 3) network level protection. Unlike computers, SHDs lack power and computing resources to apply device-level protection [31], [32]. Considering the lack of first-line defence mechanisms, the third objective of this research is to apply a second line defence mechanism. The research proposes that by isolating the SHDs and applying network-level protection, the attack surface can be reduced. Studies suggest that Firewall, IDS, and IPS as solutions to the threats occurring at the network layer [33], [34]. A security solution that both acts as a Firewall and that has the capability of an IPS is deployed. The objective is to segregate devices into separate zones and by apply access rules such communications among the IoT and non-IoT devices are curtailed. Tests are performed to validate if the artefact could successfully reduce the attack surfaces of the SHDs.

II. Background Information

The OWASP Project provides an overview of the top 10 security issues [22] found in IoT. This can be taken as a guideline to assess the type of insecurities found in SHDs. Especially, insecure network services that is ranked as a serious security issue pertains to the unneeded or insecure services in the device. Such a vulnerability can impact Confidentiality, Integrity, and Availability.

itaThreats to SHDs need not always arise from the internet; As proved by Chan et al. [35] a threat actor who has access to the internal network can misuse a vulnerability for larger attacks. As pointed out by Loi et al. [16], lack of vigour in fixing vulnerabilities in devices, lack of awareness among consumers about potential risks, and lack of network isolation or separate security solutions in home networks are seen as incentives by threat actors. With access to LAN, malicious actors may not only fingerprint every device using tools but also launch passive or active attacks.

The first aspect of this research is focussed on analysing the network-level vulnerabilities in Philips Hue Smart Light and Nest Protect Smoke Alarm. The work of Loi et al. [16] informs that both the Hue Light and the Nest Protect have open TCP and UDP ports and that the Hue Light is more vulnerable. In the case of Philips Hue, the authors indicate that the open TCP port 80 is the vulnerable port. This claim is further supported by CVE-2018-7580 [36] that a SYN-Flood DoS can result in an consume resources of the Philips Hue in an uncontrolled manner, resulting in unavailability of service. The SYN-Flood which is a Protocol based attack exploits the TCP 3-way Handshake by flooding the endpoint with excessive SYN packets. When the OS exceeds the threshold of concurrent connections it can maintain, it denies access to TCP services [37].

Network tools such as ‘hping3’ aid in generating large number of packets against a target [38], and when proper security measures are not employed, such floods result in unavailability of service – in this case a user may not be able to switch on/off the smart lights. Although the vulnerable TCP port 80 was reported for SYN-Flood, what other forms of attacks or information can be gathered from this open port is question that needs to be addressed. TCP port 80 falls under the well-known ports category [39], denoting that a server providing http service is listening on this port. Hence, this vulnerability not only allows a threat actor to conduct a Protocol DoS but also an Application Layer DoS against the device.

In the case of Nest Protect Smoke alarm, Loi et al. [16] state that numerous UDP ports in the ‘registered ports’ category remain open. Their work does not provide specific information about these ports and the functions. This research includes finding more information about those open ports and other direct flood attacks that impact the Nest Protect.

Although identifying open ports in each SHD provides information about the associated protocol and service, this process must be augmented with the capture the network traffic. This is the second aspect of this research. Capturing network traffic with packet sniffing tools such as Wireshark provides more insights. By studying the ingress and egress traffic of the devices, one can chart out not only the device, domains, and services contacted but also the frequency of such conversations. This research involves capturing traffic for both the Philips Hue and the Nest Protect and presents the baseline behaviour of these devices.

The third aspect of this research discusses about the impact of SHD vulnerabilities on a network, in general. As mentioned in the first paragraph, typically, home networks are ‘flat networks’ without any segmentation or isolation. This model in which traditional computers coexist with SHDs only increases security concern. Without isolation a compromised device can inflict damage on other IoT and non-IoT devices. Hence, this research proposes a solution that applies not only for the Philips Hue and the Nest Protect, but also for SHDs in general. By identifying vulnerabilities, understanding network traffic patterns, and by isolating IoT devices and applying a firewall the attack surface can reduced.

III. Examine, Attack, and Implementation

This research aims to identify network-layer vulnerabilities affecting the 'Availability' of Philips Hue and Nest Protect. The objective of this study is to evaluate the security of the Philips Hue smart light system and the Nest Protect smoke detector alarm as network-connected devices. The research begins by examining these devices using open-source tools to identify vulnerabilities and understand how they impact the devices' services and other connected devices. By using Philips Hue and Nest Protect as case studies, this study seeks to provide insights into the broader challenges of securing smart home devices in networked environments.

The Philips Hue Bridge version 2.1 functions on Mains power supply, connects to the network using Ethernet, and communicates with bulb using Zigbee protocol [36]. The Nest Protect is a second-generation smoke alarm that is powered by batteries, connects to the network using the IEEE 802.11 b/g/n 2.4GHz Wi-Fi standard, communicates with smartphones using BLE, and exchanges information with other connected Nest products using the IEEE 802.15.4 2.4 GHz standard [8].

The heterogeneity of IoT devices is quite evident that the SHDs used in this research vary in terms of power and communication technologies. Such heterogeneity, consequently, has a bearing on the lab network setup used for assessing the SHDs. For security reasons, the lab setup uses dedicated desktop, laptop, and networking devices.

A. *Examining the Philips Hue Smart Lighting*

As shown in Fig. 1, the TP-Link Archer C60 wireless router acts as a gateway and leases IP addresses. The TP-Link TL-SG108E switch has built in functionality for port mirroring and is used for traffic capture. Kali Linux 2023.2 which has the tools to examine the Hue Bridge is installed on the Raspberry Pi 4B. The Hue App to control the smart bulbs is installed on an iPhone 6s running iOS 15.7.x. Devices that require authentication are configured with a 12-character password that includes uppercase and lowercase characters and numbers.

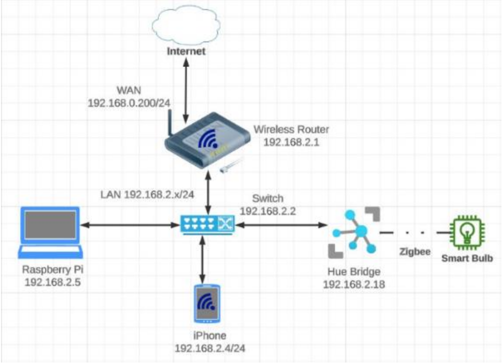


Fig. 1. Network setup – hue port scan and packet capture.

From the Raspberry Pi, a subnet scan was conducted. The network ports that are open in each of the five devices mentioned above are listed. TCP ports 80, 443, and 8080 are open in the Hue Bridge. Using the Nmap scan options -sS and -sT, a TCP SYN and TCP Connect scans are conducted. Using the -p switch, ports 1-65535 were scanned. Results show the same set of open TCP ports as the subnet scan. Further investigation carried out using an Nmap command with switches -sC -sV -O against the Hue reveals the 'Service' listening on the open TCP ports. As opposed to the SYN and Connect scan, the Fingerprint scan includes only the 1000 most popular ports. A web server is listening to TCP port 80, 443, and 8080. Out of these three open ports, 80 and 8080 use the plaintext HTTP whereas 443 uses SSL – a protocol that uses encrypted link between the client and the web server [37].

All the above scans have listed information only about the TCP ports. However, UDP based open may also be employed in this device. To find the open UDP ports we conduct a UDP scan using Nmap with the -sU switch. UDP scans can be very slow, scanning 65535 ports took around 18 hours. The UDP scan reveals three more open ports (1900, 5353, and 5540).

B. *Examining Network Behaviour of the Philips Hue Smart Lighting*

Taking advantage of port mirroring, ingress and egress traffic of the Hue Bridge was captured using both TCPDump and Wireshark. Traffic was captured based on 4 scenarios – 1. Powering on the Hue Bridge, 2. Idle Operation for 60 minutes, 3. Switching ON/OFF the bulbs using Wi-Fi, and 4. Switching ON/OFF the bulbs using 4G mobile data.

As the Hue Bridge begins to operate, it contacts the domains, almost all the domains/services are Cloud-based services hosted by AWS, Google Cloud, and Alibaba Cloud. The packet capture was repeated on different days, and it was observed that although the domains contacted were the same, the Public IP Addresses of those providers did not remain a constant. Although this observation did not hold for all the services hosted on Google Cloud, it holds true for services hosted on AWS.

HTTP traffic was found only at two instances 1) During the initial pairing between the Bridge and the smartphone and 2) At regular intervals between the Bridge and the domain www.ecdinterface.philips.com. Investigating the HTTP traffic between the Hue Bridge and the Cloud-service, reveals the type of device, its MAC address, and Public Key details. This is seen as a vulnerability as this can be of value to a malicious actor eavesdropping on the network.

C. *Vulnerabilities of the Philips Hue Smart Lighting*

As discussed above, the Philips Hue has TCP ports 80, 443, 8080 and UDP ports 1900, 5353, and 5540 open. The number of open ports may signify more vulnerabilities, resulting in an increased the attack surface. Loi *et al.* [16] in their research have stated that TCP port 80 in the Hue is vulnerable, and from CVE-2018-7580 [36] it is evident that a SYN-Flood against port 80 render the Hue unresponsive.

The SYN Flood is a technique that misuses the TCP 3-way handshake by sending large amounts of SYN packets to an endpoint. The device responds to each SYN packet and keeps waiting with open connections expecting a graceful connection closure. On the contrary, the closure may not arrive, resulting in exhaustion of resources and denial of new connections.

We have also validated this technique by creating test environment that includes three virtual computers running Kali Linux, Ethernet Switch that supports Port Mirroring, Hue Bridge, and the smartphone with the Hue App (see Fig. 2).

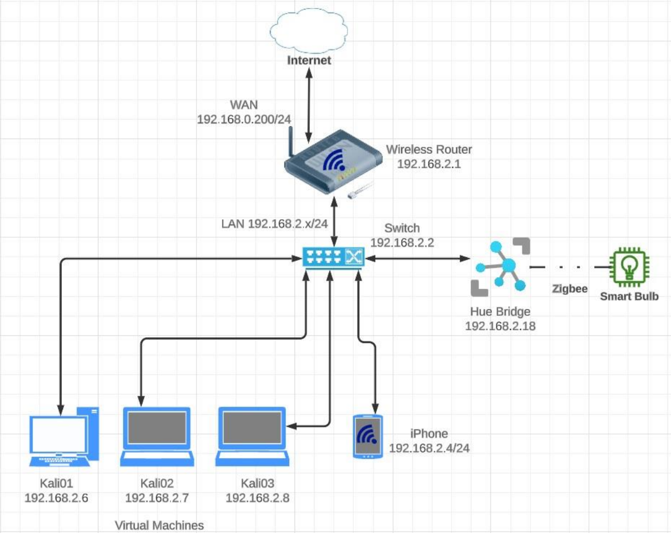
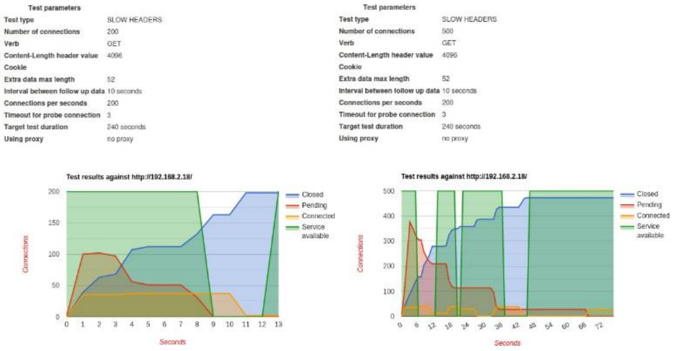


Fig. 2. Lab setup for DoS attack.

It is interesting to note that the first two sets of SYN-Floods which had a count of 500 and 750 from each machine did not have any effect. Despite the excessive amount of traffic, the Bridge and Hue App continued to remain functional throughout the test. However, in the case of the third test in which the count was raised to 1000, the impact rendered the service unavailable.

Two sets of SYN-Flood from each virtual machine was launched against TCP port 8080. However, there was no impact on the 'Availability' of the service. This proves that, with respect to SYN-Floods, TCP port 8080 is indeed the vulnerable port (Loi et al., [16]). Additionally, Hue can be subjected to HTTP and ICMP attacks. 'SlowHTTPTest' is a tool that simulates Application Layer DoS attacks and is part of Kali Linux. Using this tool two DoS attacks with 200 and 500 connections were launched, both tests disrupted the availability of the service (see Fig. 3).



Test parameters

Test type	SLOW HEADERS
Number of connections	200
Verb	GET
Content-Length header value	4096
Cookie	
Extra data max length	52
Interval between follow up data	10 seconds
Connections per seconds	200
Timeout for probe connection	3
Target test duration	240 seconds
Using proxy	no proxy

Test parameters

Test type	SLOW HEADERS
Number of connections	500
Verb	GET
Content-Length header value	4096
Cookie	
Extra data max length	52
Interval between follow up data	10 seconds
Connections per seconds	200
Timeout for probe connection	3
Target test duration	240 seconds
Using proxy	no proxy

Fig. 3. DoS attack results.

An important observation that has not been mentioned in research articles is that the Hue Bridge suffers from ICMP Flood. Three sets of ICMP Flood tests were conducted from the virtual machines and the service was unavailable during each test. Loi et al. [16] state that the Hue Bridge remains protected from ICMP DoS. However, the test result shows that the impact of ICMP flood is worse compared to SYN and HTTP Floods.

D. *Examining Nest Protect Smoke Alarm*

In contrast to the Hue Bridge, the Nest Protect uses Wi-Fi and not Ethernet. Hence to address this the lab setup was changed to conduct the Port Scans and Traffic Analysis. As shown in Fig. 4, the Raspberry Pi was used as a Wi-Fi Access Point to which the Alarm and the smartphone connect. With this setup, traffic passing through the WLAN adapter can be captured.

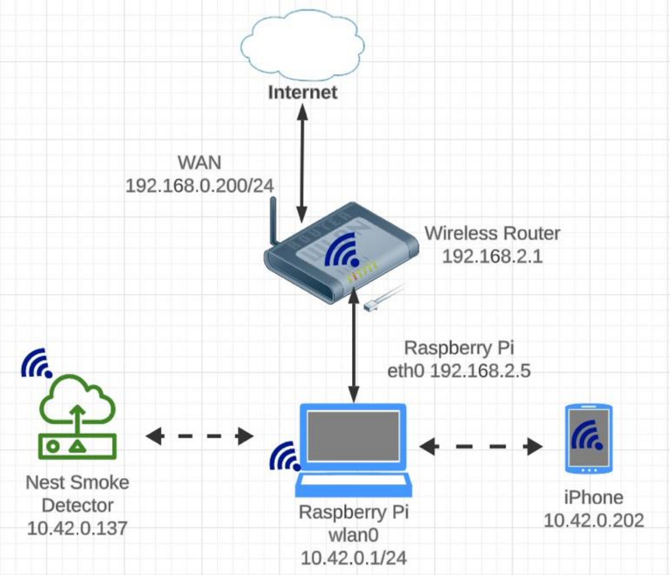


Fig. 4. Lab setup for Nest Protect.

During the initial phases of testing, it was observed that TCP SYN, Connect and Fingerprint scans did not yield any result. It was assumed that all the ports in the Nest Protect Alarm were either filtered or closed. A Ping scan of the subnet would result in displaying two hosts - the Raspberry Pi and the smartphone, but not the Alarm. It was assumed that the manufacturer had also locked ICMP Request/ Reply. Later, during a second round of analysis, it was found that the Nest Protect remains awake only for a duration of 120 seconds and goes to sleep-mode. By pressing the button on the smoke detector, the device is again activated, and communication is restored. During sleep-mode, network communication is cut off, possibly, as a power saving measure. TCP scans were set to defaults and performed within 120 seconds of each activation. It can be noted that the IP addresses of the devices during the initial phase and the second phase are different since the test environment was set up again. In contrast to the results present by Loi et al. [16], the targeted UDP port scans were not able to find any open ports in the 17000-20000 port range. It is assumed that the manufacturer must have closed these ports in a software update.

E. Examining Network Behaviour of Nest Protect Smoke Alarm

Unlike Philips Hue, both the Nest smoke detector and the smartphone app contact Cloud services. Certain surprising observations from traffic analysis reveal that the Nest smoke detector generates comparatively very less traffic – also validated by Yadav *et al.* [30]. This condition is true even when a safety check is initiated. The only HTTP traffic that was observed was between the alarm and clients.l.google.com. Rest of the traffic generated from the alarm were only TCP that used Dynamic port numbers at the source and Registered port 11095 at the Cloud servers. Further investigation reveals that Nest Protect uses the 'Weave' protocol to connect with its Cloud servers [40].

The smartphone with the Nest App makes an alarming amount of NTP requests to Google's Time Servers. However, the Nest App uses only TCP and TLS encrypted communication to all the servers it contacts. The communication with the alarm occurs only when it is active or manually invoked by pressing the button on the alarm or by using the App. The alarm does respond to ICMP until the time it is active.

From this section, it can be inferred that by comparison the Philips Hue has more open ports than the Nest Protect. This translates to more vulnerabilities and increased attack surface. In the next section, DoS attacks will be launched against the Philips Hue and the Nest Protect Alarm, and the impact of those attacks will be recorded. Solutions to reduce the attack surface and mitigate the attacks are implemented and their efficiency is validated.

F. Vulnerabilities of the Nest Protect Smoke Alarm

Compared to the Hue Bridge, it can be claimed that the Nest Protect Alarm has a lower attack surface. Since the Nest Protect does not reveal ports and services in use, it is difficult for a threat actor to attack. However, the Alarm is still vulnerable to ICMP Flood. During an ICMP Flood the Nest App could not establish a connection with the device. However, the device remains active only for a duration of 120 seconds and the chances of successful ICMP Flood attacks remain slim. As stated by Notra et al. [41] the Nest Protect Alarm is indeed a secure product. It is possible that the Nest Protect could be vulnerable to sleep-depravation attacks, but those attacks are beyond the scope of this research.

G. Implementing Solutions to Secure SHDs

Securing a device is a two-fold process – host-based security and network-based security. SHDs lack built-in security owing to their size, computational power, and power consumption. This means that unlike computers security cannot be enhanced using host-based security solutions. Also, any shortfall in security, such as open ports or unnecessary services cannot be fixed (Shirali-Shahreza and Ganjali, [42]). Since device-level security cannot be applied, the artefact applies the other two security approaches, 1) isolation and 2) network-level protection, as suggested by Hamza et al. (Hamza, Gharakheili and Sivaraman, [31]).

1) Isolation and network-level protection of SHDs: As the research involves real SHDs, to implement a solution a device had to fulfil certain conditions: it must be affordable, portable, must serve the Ethernet-based Philips Hue and the Wi-Fi based Nest Protect, and must fit in the existing network without major changes. Based on these conditions a Raspberry Pi 4B was chosen. To avoid license costs, a Linux Kernel based distribution was the preferred choice of OS for the Raspberry Pi. Open-source tools such as Snort, pfSense, OpenWrt, and IPFire were considered. pfSense was not tested as it supported only certain architectures. Ubuntu Desktop 22.04 LTS was installed on the Raspberry Pi as installing Snort is a straight-forward process in Ubuntu. However, owing to the sluggish behaviour of the OS and difficulties in successfully installing configuring dependent packages such as 'dnsmasq' and 'hostapd' the idea was aborted. Since OpenWrt and IPFire both were supported, both tools were installed in separate SDXC cards and tested.

Both OpenWrt (2023) and IPFire (2023) are open-source and community-supported products that ensure security by default. Both the products are compatible with the Rapberry Pi, satisfy conditions for isolation and network-level protection, and offer GUI. However, IPFire was chosen over OpenWrt as the former is designed and optimised to be a Firewall whereas the latter includes Firewall functionality. Unlike commodity Home Gateways and OpenWrt, IPFire enables HTTPs based GUI by default.

It is straightforward to choose a network configuration in IPFire that supports WAN, LAN, and WLAN interfaces required for this research. The WAN interface or the RED zone has been connected to the existing network and the SHDs are isolated from each other and from the existing home network. The Hue Bridge is part of the GREEN zone (Subnet-02 - 10.100.100.0/24) and the Nest Protect is part of the BLUE zone (Subnet-03 – 10.100.200.0/24) as shown in Fig. 5. Although the installation of IPFire in Raspberry Pi is not straightforward, it can still be achieved with support from the developer [43], a process that is easier in OpenWrt.

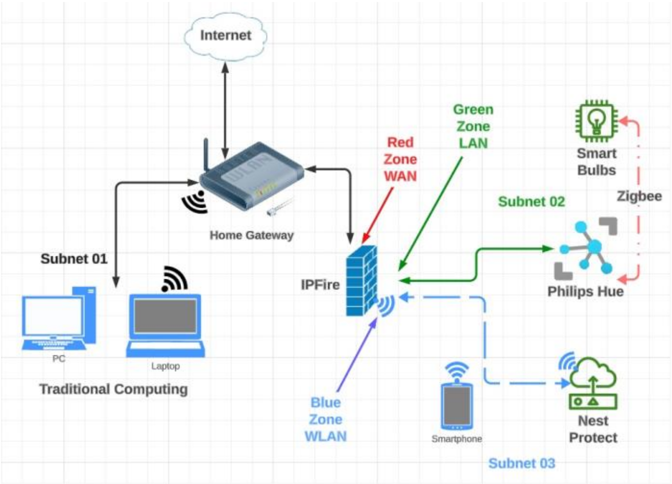


Fig. 5. Network setup and artefact placement.

Through the 'PakFire' module additional packages such as 'hostapd' which enables the Wi-Fi access point can be installed. By default, IPFire enables MAC filtering for wireless clients. Hence every new device connecting to Wi-Fi must be approved. This security features disallows rogue devices connecting to Wi-Fi. Although IPFire can be remotely accessed via SSH, as a security feature it is disabled by default.

IPFire's SPI firewall, based on 'netfilter', by default restricts traffic between the zones [44]. In addition, the Firewall provides 'IP Address Blocklists' to deal with traffic based on the reputation of IP Address [45], and 'Location Block' to block incoming connection from certain Geo-locations [46].

One of the most important features of IPFire is its ability to function as an IPS. IPFire employs Suricata [47], an open-source software for intrusion prevention [48]. Although, this feature is disabled by default, it can be enabled on more than one interfaces. Traffic passes through the IPS before it is sent to the Firewall, and malicious traffic is dropped by the IPS. IPS works based on 'Rulesets' and IPFire allows an user to choose more than one ruleset. Some community rulesets are free whereas some need add a subscription. By this, IPFire achieves the functionality of Snort IPS. The Firewall, IP Blocklists, and IPS have separate logs that can be accessed through the GUI. Connections are tracked and are displayed in the GUI. In addition, CPU load, Memory usage and Processes are displayed graphically [49].

IV. Conclusion And Future Work

Smart Home systems are becoming more popular and the rate of adoption of these devices has been tremendous. SHDs make our life easier by allowing physical devices to be controlled over the internet. However, SHDs may have vulnerabilities and can introduce new challenges to home network security. The DDoS attack against Dyn that was conducted using compromised consumer IoT devices is proof that smart devices can participate in larger attacks.

Typically, IoT and non-IoT devices coexist in home networks. In many cases SHDs remain unmonitored and consumers are unaware of the security issues that may exist in these devices. Weak authentication methods and insecure network services have been the top security issues found in IoT devices. Hence, it is imperative to study the insecurities in SHDs and deploy security solutions to reduce the attack surface.

Vulnerabilities may reside in any of the three layers in the IoT architecture. However, this research focussed in identifying the vulnerabilities at the network layer. A test lab was setup to examine the Philips Hue and the Nest Protect. The baseline behaviour of each of these devices were recorded. It is evident that both the devices depend on various Cloud-hosted services. Although both the devices use secure protocols and encrypt application data, the Philips Hue still uses HTTP based communication to a cloud service.

The research then involved Nmap port scans which revealed the open ports and the associated services. Abusing these ports and services by sending excessive amounts of traffic can directly impact the 'Availability'. This was demonstrated by conducting volumetric flood attacks against the Philips Hue. Owing to open ports, a threat actor can launch SYN Flood, HTTP Flood, and ICMP Flood against the Philips Hue, turning the device unresponsive.

On the other hand, services such as UPnP that advertise the capabilities of a device on the network can be misused, exposing devices to the internet. In the case of the Philips Hue, the UPnP service exposes the device's unique identifiers. Such details can result in spoofing attacks. It is evident that the Nest Protect alarm is, comparatively, a safer device as it does not expose its ports and services. Still, an ICMP Flood launched against the Nest Protect turned the device, temporarily, unresponsive. It is possible that the Nest Protect can suffer from sleep deprivation attacks, however such attacks were outside the scope of this research.

Unlike computers, IoT devices cannot be protected using device-based security solutions. Hence, the focus was shifted to protecting these devices through isolation and applying network-level protection. In addition, the Philips Hue and the Nest Protect are heterogeneous – the former uses Ethernet and the later Wi-Fi for communication. Hence the solution must encompass both standards. Deploying IPFire, a powerful open-source Netfilter based SPI Firewall on a portable device like Raspberry Pi 4B fulfils the requirements. IPFire separates the flat home network into three zones, and by default curtails communications between the LAN and WAN zones. Through Firewall rules, it was demonstrated that complete isolation between LAN and WLAN zones can be achieved.

Unlike commodity Gateways and Wi-Fi Routers, IPFire neither has in-built UPnP nor does it allow the service to be installed. This ensures that malicious programs cannot open ports without user consent. The Suricata IPS engine is one of the important aspects of IPFire since packets are analysed by the IPS and any malicious traffic is dropped before reaching the firewall. This feature ensures that only legitimate traffic reaches the SHDs. In addition, IP Blocklists can also be configured to drop traffic from IP Addresses with poor reputation. IPFire by default enables DNSSEC and the user can enable DNS over TLS. Such features reduce the chances of DNS spoofing and cache poisoning. With these features, IPFire reduces the attack surface of the Philips Hue and the Nest Protect. Although deploying a Firewall and IPS ensure security, improving the efficiency of such systems is a continuous process that involves scrutinising the Firewall and IPS logs and applying relevant rulesets.

Insecurities exist in all layers of the IoT architecture, but this research was limited only to the network layer and to certain types of DoS attacks. In the future work, sensing layer related vulnerabilities will also be included. Another limitation is, IPFire supports only IP address-based access rules. A Firewall that supports Fully Qualified Domain Name (FQDN) based rules will involve less overhead since Cloud providers tend to assign various public IP addresses for hosted services. The methods followed in this research can be expanded to include other devices. Hence, the future work will include devices such as the Smart TV.

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Texture and Color Descriptor Features-based Vacant Parking Space Detection using K-Nearest Neighbors

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***Abstract*—The importance of the detection of vacant parking spaces is increasing gradually. A system capable of detecting vacant parking spaces in real-time can play an important role in saving valuable time for motorists, decreasing traffic jams, and reducing air pollution. Vision-based parking space detection methods are advantageous in terms of installation and maintenance as existing security cameras in a parking area can be used without the requirement of additional hardware and the detection program can be run on a local or a remote server. One major problem of the vision-based detection method in this context is making the model generalized for detection in various weather conditions. This research proposes a hybrid method to detect vacant parking spaces that use texture and color descriptors. A weighted KNN is used for the classification of parking spaces. The proposed method experimented on PKLot, a large benchmarking dataset that contains images of three parking areas in three weather conditions. The proposed model achieves an accuracy of 99.47% on average while training with 10-fold cross-validation and achieves an accuracy of 99.41% accuracy on average while testing with unseen data. The model shows robustness and better performance in terms of accuracy and processing speed. Several comparisons are also done to show how well it performs with methods found in previous research.**

Keywords*—*Texture; color descriptor; k-nearest neighbors; computer vision; image processing

I. Introduction

The requirement for vehicle parking space is increasing due to the increasing number of people owning vehicles causing unbalance in demand and supply of parking spaces. In addition, another underlying reason is the number of parking spaces in a certain location is fixed but the demand for parking spaces varies at different times of the day. People may not be able to locate parking spaces even after spending significant time looking for one during rush hours. Utilization of the available parking space efficiently can be a key solution in this regard where motorists will need real-time information of the available parking spaces of the nearby parking areas. In this context, the necessity of automatic vacant parking space detection is a demanding research topic in the field of computer vision domain. Vision-based automatic vacant parking space detection can help to find available parking spaces at certain locations using images from preinstalled cameras in a parking area.

Previous researchers proposed various approaches to solve vacant parking space detection, i.e., various sensors-based detection [1, 2], counter-based detection [3, 4], and vision-based detection [5, 6, 7]. Wireless sensors were previously used to develop parking monitoring systems but the problem with the sensor-based method is that deployment and maintenance of sensors are required also the sensors add additional costs [2]. Counter-based methods keep track of the number of vehicles entering and exiting the parking area, however, counter-based methods cannot provide information about parking space location which cannot be used for a wide range of applications [4]. Although previously some research criticized the vision-based approaches technique because of expensive camera equipment and the need to deal with a large amount of data [6], a vision-based vacant parking space detection system can easily be deployed using existing security cameras of the parking space without additional hardware requirements in parking area [7]. This research focused on detecting vacant parking spaces using texture analysis based on Gray Level Co-Occurrence Matrix (GLCM) also known as Grey Tone Spatial Dependency Matrix and RGB color descriptors. The proposed method was validated using the PKLot dataset [7] which is a large dataset of three parking areas with different weather conditions and different times of the day. PKLot dataset was previously used for validating various previous methods, i.e. CarNet [8], mAlexNet [9], and Deep CNN [10] which are compared with the proposed method based on various performance metrics.

The rest of the research paper is structured as follows: Critical previous research is illustrated in the background study, mentioned in Section II, comprehensive details of the proposed methodology are elaborated in Section III, details of experimental results with analysis for experimental validation are demonstrated in the experimental results and analysis in Section IV and finally, the conclusion in Section V presents concluding remarks.

II. Background Study

Several research has been done to solve the parking space detection problem while keeping three factors in consideration, i.e., mind robustness, deployment effort, and maintenance cost. Previous research has been conducted resulting in different methods i.e., multicamera vehicle detection [11], drone-based and aerial image analysis [12, 13], image descriptor-based [14], geometric features-based [15], edge-based [16], plane-based [17], convolutional neural network [18, 19], sensor network [2] [20]. Some of the previous research was done based on wireless sensor networks. Sensors are being placed in parking spaces to transmit data to a server to detect if space or unoccupied is occupied [2] [20]. However, existing related methods related to sensors, cost, and maintenance were not feasible in large parking areas. Currently, researchers are more focused on vision-based parking space detection where images of the parking area are taken using the camera. Research in [21] used two types of approaches for image-based systems, one of them was car-driven and another one was space-driven. In the car-driven approach, methods were developed to detect cars as objects as the main objective. However, the problem with this approach was that when a camera was placed at an angle, images of vehicles near the camera and far from the camera have a significant difference in quality as the number of pixels will be less for far images. So, the detection of objects or vehicles became complex. In the space-driven approach, the detection of space was the main objective. The space-driven approach was less complex than the car-driven approach because space has more similarity than vehicles at a particular place. However, the challenge of the space-driven approach was to create robust methods for different parking areas under different scenarios.

Research in [15] proposed a geometric feature-based method to detect vacant parking space where a line segment was used to detect an algorithm for creating a line-clustering method consisting of several parallels for separating lines with a fixed distance and one guideline. The false line was removed and then the guideline was detected using a learning-based method. This method performed better than the single bird's eye view method proposed by research in [15]. However, this method was unable to meet real-time processing. Research in [13] used aerial images and line detection and combined selective filtering calculated using the prevalence of line length and angle. Their algorithm aimed to do automated detection of parking space regions in parking lot images for collecting parking occupancy information. The advantages of this method have four aspects, i.e., provided well enough results for automatic region extraction, fast, covered a large area, and can be used for automatic segmentation. However, some lines were not detected by that method due to light and shadow variance. Research in [22] used a deep convolutional network by introducing an architecture called "Siamese architecture" for learning robust features of the parking spaces for eliminating inter-object occultation and increased performance in various illumination conditions. They also used three space input patches of a single parking space and trained the network for the classification of parking occupancy. The method proposed by research in [22] was better than the method proposed by research in [13] due to the usage of a drone coupled with a line detection algorithm to detect parking space which was not robust, and the deployment and maintenance would be more difficult than just using single or multiple fixed place cameras. In addition, research in [22] performed better in different illumination conditions wherein research in [13] method of light and shadow variance caused problems in line detection.

Research in [11] proposed a method based on dilated convolution neural networks. They claimed their model to be more robust than other methods proposed by research in [14] and [16]. Research in [8] used the dataset that was created by research in [2] named PKLot and compared the results with other research methods. There was a significant difference when the dataset was trained in one parking lot and tested in other parking lots. Results by research in [5] showed that their method was more robust as their accuracy did not fall like previous research while training and testing in different datasets. In this context, research in [7] used two texture-based features, i.e., local binary patterns and quantization of the local phase. Support Vector Machine (SVM) was trained in their research to detect vacant parking spaces and received an accuracy of 99% when the model was trained and tested on the same dataset. However, for other datasets, they achieved the best accuracy of 89% using textural features. The method proposed by research in [5] performed better than research in [7] in terms of robustness. Experimental results by research in [8] showed that their proposed method accuracy did not fall like research in [7] while training and testing in different datasets.

Existing research methods need to be robust for parking space detection in terms of various illumination and environmental conditions like sunny, cloudy, and rainy. In addition, these methods need to be easily deployable, and maintenance should be cost-effective. The method proposed by research in [15] was able to provide real-time parking space detection. However, that method cannot be used for a large number of parking areas because outdoor parking areas contain a large number of parking spaces. Research in [13] used aerial images for the detection but using a drone is not cost-effective and not suitable for daily use as the drone has a very limited battery life and high maintenance cost. Research in [22] used fixed-place cameras to detect vacant parking spaces, they used three space input patches of a single parking space detection using CNN and were able to achieve good accuracy. However, research in [7] used only a single patch and texture-based features for the detection which claimed to be performed better compared with research in [22]. Research in [7] and research in [18] lack in terms of robustness because despite providing good accuracy on a single parking area, their accuracy decreased when multiple parking areas were used in the scenario. This research proposes an efficient method for parking space detection using texture and color-based features to make the validation robust. In addition, the proposed method is easily deployable and has low maintenance costs as it can be deployed using the camera that already exists in parking areas.

III. PROPOSED METHODOLOGY

The proposed method aims to detect vacant parking spaces in different weather and illumination condition of the day shown in Fig. 1. The proposed method mainly focuses on the extraction of features that reflect the difference between unoccupied and occupied parking spaces. The overall methodology consists of four steps, i.e., acquisition of images for processing, segmentation of parking spaces using a fixed mask and preprocessing segmented images, color descriptors-based feature and texture-based feature extraction, and detection of parking spaces using supervised machine learning algorithm k-nearest neighbors. The proposed method by this research is depicted in Fig. 1.

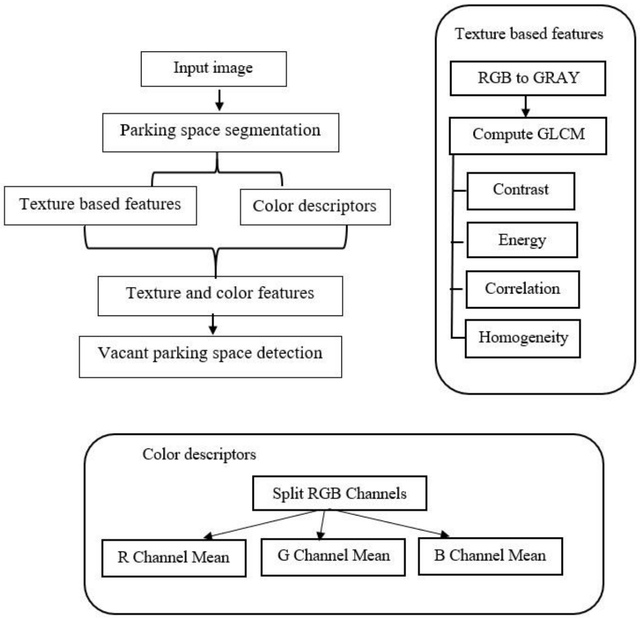


Fig. 1. Proposed method.

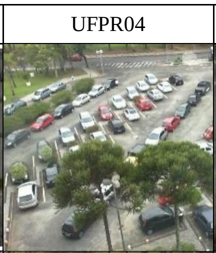
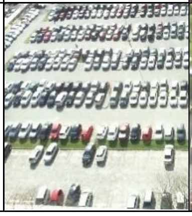
A. *Input Image*

This research used the PKLot dataset of three different parking areas. According to research in [7], a single camera covering the whole parking area was enough for the detection of vacant parking spaces. The dataset was annotated with information of the locations of parking spaces and occupancy status. In terms of real-life use, camera calibration was followed as research in [4] [23]. PKLot Dataset consists of three subsets for three parking spaces, i.e., PUCPR, UFPR04, UFPR05, and images of three different weather conditions sunny, cloudy, and rainy for each parking area. Sample images of the PKLot dataset are mentioned in Table I.

B. *Parking Space Segmentation*

The parking area may consist of many parking spaces. For this reason, automatic segmentation of parking space will produce extra computational overhead and causes the process not suitable for real-time use. For faster segmentation, a fixed mask once for all spaces was created manually as research in [7] and [24] did in their research which leads them to achieve very fast segmentation of parking spaces. The fixed mask uses the coordinates of the parking spaces. After placing the camera, coordinates of the parking spaces were collected to crop out the patches of the parking spaces from images. The terminology is that for a fixed camera, the parking spaces are static, only a vehicle will move into a parking space or will move out of one. Two copies of a segmented parking space were created for two types of feature extraction, i.e., color feature-based and texture feature-based extraction. For color-based feature extraction in preprocessing part, a segmented RGB parking space is split into three channels R, G, and B as the intensity of the pixels also varies on different channels. The R, G, and B channels of occupied parking space have more variations than the unoccupied parking space, also there is a significant difference between occupied and unoccupied R, G, and B channels, and can be used as features to distinguish between occupied and unoccupied parking spaces. After color-based features, texture-based features were extracted for the highly distanced parking spaces from the camera which are smaller than less far parking spaces from the camera in addition, highly distanced parking make the structural or geometrical features extraction more complex and not effective but texture-based features can be used to find the similarities and dissimilarities between occupied and unoccupied parking spaces in that scenario. For texture-based feature extraction, images were converted RGB to grayscale followed by median filtering. Details of features extraction regarding color features extractions and texture features extractions are explained comprehensively in the next section.

TABLE I. SAMPLE IMAGES IN DATASETS

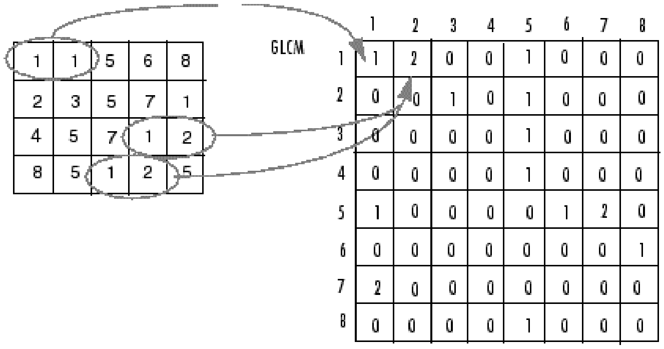
	PUCPR	UFPR04	UFPR05
CLOUDY			
RAINY			
SUNNY			

C. *Color Descriptors and Texture-based Features*

This research used texture features-based information of the parking space which were collected from the Gray Level Co-Occurrence Matrix and combining them with color-based feature helped to achieve more accuracy and even if the parking space was near or far from the camera, they had similar values and leading to more robust methodology comparing with the previous research. In this section, color descriptors-based features and texture based-features were extracted. For color descriptors-based features, there is a significant difference in occupied and unoccupied RGB channels. Using Eq. (1), the mean value of each channel is calculated to estimate significance difference in occupied and unoccupied RGB channels.

$$\bar{k} = \frac{1}{z}\sum_{j=1}^{z} k_j \qquad (1)$$

where, k¯is the mean of a channel and z is the number of pixels and k_j is the value of the intensity of a pixel. For texture-based features, Gray Level Co-Occurrence Matrix (GLCM) was used to derive some statistical values of the images. The GLCM is constructed from gray images. GLCM has rows and columns that are equal to the number of tones or gray levels in a grayscale image. In addition, GLCM calculates how often a gray tone or intensity occurs with the adjacent pixels from the input image.



1	1	5	6	8
2	3	5	7	1
4	5	7	1	2
8	5	1	2	5

	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

Fig. 2. GLCM construction example for 8-tone grayscale [25].

Fig. 2 shows the calculation of GLCM of 8 tone grayscale images, but in this research, GLCM was calculated for 256-tone grayscale images. GLCM can extract certain texture properties from the spatial distribution of the gray image. In the proposed method by this research, four statistical texture features were computed from the GLCM matrix, i.e., Contrast, Correlation, Energy, and Homogeneity. Various texture features were extracted based on Eq. (2) to Eq. (5) [26].

$$C = \sum_{m,n=0}^{L-1} Q_{m,n}(m-n)^2 \tag{2}$$

$$\mathrm{D} = \sum_{\mathrm{m,n=0}}^{\mathrm{L-1}} \mathrm{Q_{m,n}} \frac{(\mathrm{m}-\mu)(\mathrm{n}-\mu)}{\mu^2} \tag{3}$$

$$E = \sum_{m,n=0}^{L-1} (Q_{m,n})^2 \tag{4}$$

$$H = \sum_{m,n=0}^{L-1} \frac{Q_{m,n}}{1+(m-n)^2} \tag{5}$$

where, L = number of intensity levels, Q_{mn}= element at (m,n), μ = mean of GLCM, σ^2= intensity variance. Thus, the proposed method dealt with multiple features which were extracted and used for the detection of vacant parking spaces by manipulating the correlation among these multiple features.

D. Vacant Parking Space Detection

The proposed method extracted features represented as numeric values collected from many images from subsets of the PKLot dataset with three different weather conditions. Several classifiers, i.e., logistic regression, Support vector machine, k-nearest neighbor, weighted k-nearest neighbor, and linear discriminant were tested to check how these classifiers perform on the features extracted by this research. Among all the classifiers, the weighted k-nearest neighbors algorithm worked well for the classification of parking space. The parameters used for the model are shown in Table II.

Due to better performance and low complexity, this research used a weighted K-nearest neighbor as the classifier. As all the extracted features are numerical using KNN which makes training and testing the model less complex. The weighted KNN model was trained and tested with the features that were extracted using the proposed methodology. As the supervised machine learning algorithm needs labeled data, vacant information was collected from the PKLot Dataset [7]. Classified parking spaces were marked as green for unoccupied ones and red for occupied ones shown in Fig. 3 as a result of the proposed method.

TABLE II. PARAMETERS USED FOR WEIGHTED KNN

Parameters	Value	Formula
Distance Metric	Euclidean	$d = \sqrt{\sum_{i=1}^{n}(x_i - y_i)}$
Distance Weight	Squaredinverse	w= 1/d^2
Break ties	Smallest	-
Number of Nearest Neighbors	10	-
Nearest Neighbor Search Method	kdTree	-

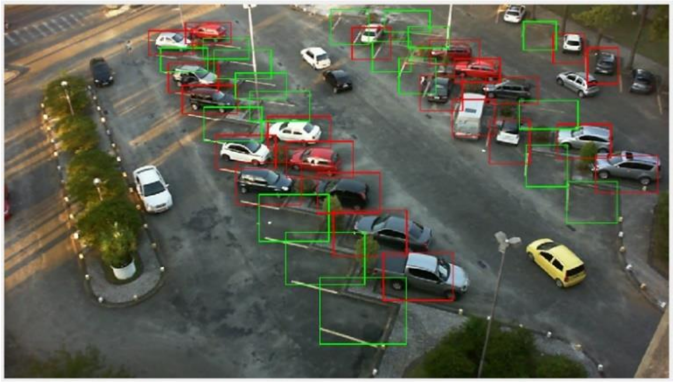


Fig. 3. Classified parking spaces UFPR05-Sunny.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

This research was validated using several phases during experimentation shown in Fig. 4.

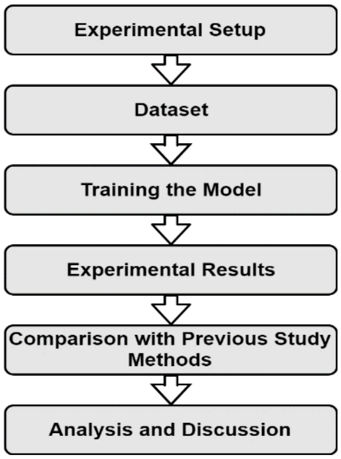


Fig. 4. Experimental framework to validate the proposed method.

A. Experimental Set Up

Proposed method experimented on the environment with a hardware configuration of Intel(R) Core (TM) i7 CPU540 @ 3.07GHz (4 CPUs) ~3.3GHzProcessor, 16GB RAM, Windows 10 64-bit operating system, and MATLAB R2019a. MATLAB provides a very good environment for rapid prototyping and debugging. MATLAB's image processing and machine learning environment provide an efficient set of optimized functions to make the workflow faster. The proposed method requires the parking area image as input and outputs the classified parking areas as green and red.

B. *Datasets*

The proposed method is experimented using the dataset PKLot [7] for validation. There was a total of 653169 numbers of observations extracted from the actual dataset out of which 72,000 observations are used as training samples. Out of 72,000 observations shown in Table III, 24,000 observations are used from each of the parking areas such as Pontifical Catholic University Paraná - Parking Lot (PUCPR – PKLot), Federal University of Parana - Parking Lot (PKLot - UFPR04) from 4th Floor, Federal University of Parana - Parking Lot (PKLot - UFPR05) from the 5th floor. These 24,000 observations are randomly sampled from the collection of observations for individual parking areas and weather conditions.

TABLE III. NUMBER OF SAMPLES

	Samples per parking area	Number of Training Samples
PUCPR-Sunny	24,000	72,000
PUCPR-Cloudy		
PUCPR-Rainy		
UFPR04-Sunny	24,000	
UFPR04-Cloudy		
UFPR04-Rainy		
UFPR05-Sunny	24,000	

C. *Training the Model*

72,000 observations are used for training K-nearest neighbor with 10-fold cross-validation for protecting the model from overfitting and the number of neighbors or K used is as 10. After changing different values of K, this research observed that greater than the nearest neighbor value 10, the classification result did not improve and less than k = 10 sometimes leads to false classification. Hence, K=10 is chosen for training the model. Other parameters used for training the KNN model are explained below:

1) *Distance metric:* Euclidean Distance estimated the distance of edges between neighbors as K [27] for the proposed method. Neighbors are m-by-n data vectors where m denotes the number of training samples and n denotes number of features used.

The distance was measured using $d_i(u_s, v_t) = \sqrt{\sum_{i=1}^{y}(u_{si} - v_{ti})^2}$ where d$_i$ is the distance of the edges between neighbors, u_s and v_t are 1-by-y data vector of the source and destination.

2) *Distance weight:* Weight g_i associated with the training samples are estimated as the squared inverse of the distance, $g_i = \frac{1}{{d_i}^2}$ and the weighted distance is calculated as

$$d_{gi}(u_s, v_t) = \sqrt{\sum_{i=1}^{y} g_i(u_{si} - v_{ti})^{2}}$$

3) *Break ties*: Smallest value was used to break the tie in case there were an equal number of neighbors with similar values.

4) *Number of nearest neighbors:* Nearest neighbor K=10 used to take decision of new data.

5) *Nearest neighbor search method:* A k-dimensional tree (Kd-Tree) was used to search for the neighbors [28] instead of an exhaustive method to search faster. The Kd-tree method divides a data vector of n-by-k recursively and distributes n points into a binary tree of K-dimension. Hence, the model grows a multi-dimensional Kd-tree using associated weight and Euclidean distance with a bucket size of 60 which is the maximum number of points in the leaf node [29].

D. *Evaluation Parameters*

The proposed method was validated with the test sets using various metrics, i.e., Confusion Matrix, Accuracy, Area under Curve (AUC), Error, Precision Rate, Recall Rate, Processing Time, and Processing Speed in Frame per Second shown in Fig. 5.

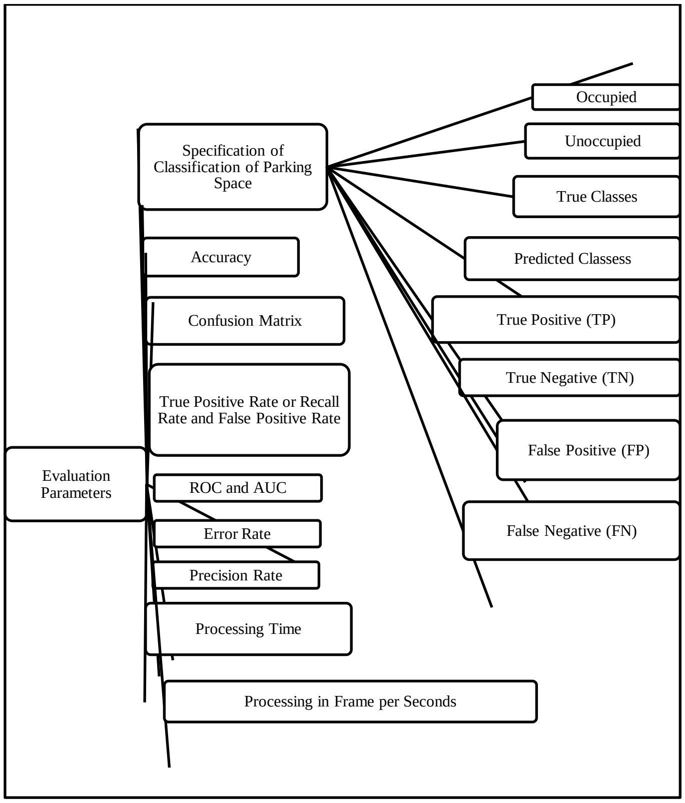


Fig. 5. Performance metrics used for validation.

1) Specification of the classification of a parking space: This research used two possible outcomes to denote the status of a parking space, i.e., occupied, and unoccupied. Occupied space refers to when a vehicle is parked in the parking area otherwise denotes unoccupied. These two statuses are considered classes for the prediction model. The true class represents the actual status of parking spaces that are known, and the predicted classes represent the status predicted by the trained model shown in Table VI to Table IX. In addition, looking for unoccupied space is considered a positive interest, and occupied space is considered a negative interest. Classifying a Positive sample as Positive is considered a True Positive (TP), Classifying a Negative sample as Negative is True Negative (TN), Classifying a Negative sample as Positive is False Positive (FP), and Classifying a Positive sample as Negative is False Negative (FN).

2) Performance metrics: The proposed method estimated the Confusion matrix which denotes the information about actual status and predicted status of training samples [30]. The performance of the trained model is commonly evaluated using the data of the confusion matrix. True Positive Rate and False Positive Rate were implicated to estimate the Receiver Operating Characteristic curve (ROC) and Area Under Curve (AUC) [31, 32]. The proposed research plotted ROC by placing the FAR on the x-axis and the TPR on the y-axis for several different observations. The values of False Positive Rate (FPR) and True Positive Rate (TPR) range from 0.0 to 1.0. A method with the best prediction skill is represented by the curve that goes from the bottom left corner to the top left corner and then towards the right top corner of the ROC plot [32]. This research also used Precision rate which denotes the rate of the positive prediction in terms of total positive prediction. Processing time was also estimated which denotes the time required to process one frame. In addition, the Processing speed in patches per second is calculated from the number of patches and the processing time taken to process them. In this context, Processing speed in frame per second represents the time to process a frame. Other performance metrics were calculated to validate the proposed method mentioned in Table IV which the corresponding equation used.

E. Experimental Results

The proposed method achieved an accuracy of 99.47% during training, which indicates better performance compared with the state-of-the-art. Table V depicts the confusion matrix of the trained model and Fig. 6 illustrates the AUC of the trained model. The total number of Positive samples (unoccupied spaces) used for the trained model is 36967 and the total number of Negative samples (occupied spaces) was 35033. Out of the total Positive samples, 36743 samples are correctly classified using the trained model, and 224 unoccupied spaces are classified as occupied. Besides, out of the total Negative samples (occupied spaces), 34895 spaces are classified as Negative (occupied), and 138 samples are identified as Positive (unoccupied). Hence, the number of FP and FN is comparatively very small compared to TP and TN which leads to higher accuracy compared with existing research.

TABLE IV. PERFORMANCE WITH EQUATION

Name of Metrics	Equation
Accuracy [30, 33]	$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$
True Positive Rate or Recall Rate [30, 34]	$\text{True Positive Rate or Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$
False Positive Rate [30, 33, 35]	$\text{False Positive Rate} = \frac{\text{FP}}{\text{FP} + \text{TN}}$
Error Rate [30, 31, 36]	$\text{Error} = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$
Precision Rate [30, 31, 37]	$\text{Precision Rate} = \frac{\text{TP}}{\text{TP} + \text{FP}}$

TABLE V. CONFUSION MATRIX OF TRAINED KNN MODEL WITH 10-FOLD CROSS-VALIDATION AND K=10

		Predicted Classes	
		Unoccupied	Occupied
True Classes	Unoccupied	36743	224
	Occupied	138	34895

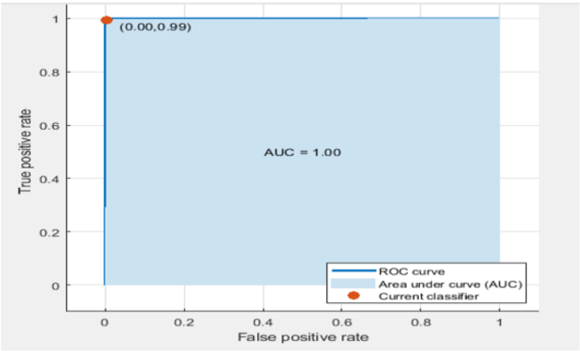


Fig. 6. Area Under Curve (AUC) at training.

Fig. 6 depicts the ROC and AUC curve for the trained model [32]. Here, the curve shown is the ROC curve, the shaded area is AUC which is ≈1and the point represents the used model. Based on the AUC value, the proposed method performed better for the training samples.

Table VI shows the confusion matrix of tested samples from PUCPR parking area images. 399118 samples were extracted from PUCPR which were used for testing the proposed method, each sample represents a parking space labeled either Unoccupied or Occupied. For the PUCPR images, out of the total samples, 211378 samples are classified as unoccupied, and 2183 samples as occupied out of 213,561 samples that were unoccupied. Again, out of 185,557 samples that were occupied, the proposed method predicted 183,890 samples as occupied and 1,667 samples as unoccupied. There were 88,266 samples from FPR04 parking area images that are used for testing the proposed method to estimate the confusion matrix shown in Table IX. For the FPR04 images, 48,700 samples were classified as unoccupied, and 512 samples as occupied out of a total of 49,212 samples that are unoccupied. Again, out of 39,054 images that were occupied, the proposed method predicted 38,754 samples as occupied and 300 samples as unoccupied. 165785 samples from FPR05 parking area images were extracted using the proposed method to estimate the confusion matrix shown in TABLE X. Proposed method classified 67,361 samples as unoccupied, and 998 samples as occupied out of a total of 68,359 samples that were unoccupied. Out of a total of 97,426 images that were occupied, the proposed method classified 96,648 samples as occupied and 778 samples as unoccupied.

TABLE VI. CONFUSION MATRIX FOR PUCPR, FPR04 AND FPR05

PUCPR		Predicted Classes	
		Unoccupied	Occupied
True Classes	Unoccupied	211378	2183
	Occupied	1667	183890
FPR04			
True Classes	Unoccupied	48700	512
	Occupied	300	38754
FPR05			
True Classes	Unoccupied	67361	998
	Occupied	778	96648

Several observations that were used from different parking areas for validating the model along with the number of prediction speeds in terms of observation/millisecond are shown in Table VII. The prediction speed on average was 23.01 observation (obs)/milliseconds(ms).

TABLE VII. NUMBER OF OBSERVATIONS TESTED AND PREDICTION SPEED

Datasets	Number of Testing Observations	Prediction Speed in o obs/ ms
PKLot-PUCPR	Cloudy = 132781	21.23
	Rainy = 83009	
	Sunny = 183329	
PKLot - UFPR04	Cloudy = 39392	24.37
	Rainy = 7951	
	Sunny = 40923	
PKLot - UFPR05	Cloudy = 56985	23.43
	Rainy = 8929	
	Sunny = 99871	

The accuracy of the proposed method for PUCPR, FPR04, and FPR05 were 99.21%, 99.91%, and 99.29% respectively shown in Table VIII. The accuracy of the three subsets does not fluctuate and it stays above ≈99%. The error rates are 0.79%, 0.9%, and 0.71% which on average stays at around ≈ 0.98%. The precision and recall rate are on average 99.16% and 98.7%. The precision rate represents the rate of the positive prediction in terms of total positive prediction which is 99.16%, and the recall is the rate of positive prediction in terms of total actual positive which is 98.7% for the proposed method.

The number of patches or parking spaces used from different parking spaces is shown in Table IX. PUCPR subset images cover many parking spots in a single image but in the experimentation, 102 parking spots were used from each image of PUCPR, 31 parking spaces from UFPR04, and 44 parking spaces from UFPR05 were used, processing a single image of PUCPR, UFPR04, and UFPR045 with total patches for each required 0.14, 0.15, and 0.17 seconds respectively. Processing speed in patches per second was calculated from the number of patches and the processing time taken to process them. Besides, processing speed in frame per second denotes the time to process a frame shown in Table IX. When the number of patches increased, the processing speed decreased in frame per second because it required more processing time.

TABLE VIII. ACCURACY AND DIFFERENT PERFORMANCE MEASURES

Datasets	**Accuracy %**	**Error %**	**Precision Rate %**	**Recall Rate %**
PKLot-PUCPR	99.21	0.79	99.27	98.8
PKLot - UFPR04	99.91	0.9	99.41	98.7
PKLot - UFPR05	99.29	0.71	98.79	98.6

TABLE IX. PROCESSING SPEED IN FRAME PER SECOND

Datasets	Number of Patches in Frame	Processing Time in Seconds	Processing Speed in Patches Per Second	Processing Speed in Frame Per Second
PKLot-PUCPR	102	0.14	44.57	0.39
PKLot - UFPR04	31	0.15	41.3	1.41
PKLot - UFPR05	44	0.17	47.21	1.09

F. Comparison with Previous Research Performance

The proposed method achieved an average accuracy of 99.47% whereas De Almeida et al. [7] achieved an average accuracy of 91.5% using the PKLot dataset as shown in Table X. In this context, the proposed method by this research achieved an accuracy of 99.47% using the same datasets. Besides, De Almeida et al. [7] used texture-based features from PKLot whereas the proposed method used texture and color descriptor features which caused better performance. CarNet by Nurullayev et al. [8] and AlexNet by Amato et al. [9] received an accuracy of 97.04% and 96.74% respectively which is lower than the proposed method. Deep CNN by Valipour et al. [10] provided an AUC (Area Under Curve) of 0.9994. In this context, AUC achieved by the proposed method is 1 shown in Fig. 6 which indicates proposed method performed better than previous research in terms of accuracy and AUC.

The proposed method requires 0.15 seconds to process a single patch or single parking space shown in Table XI. 1.048 frames was processed in 1 sec which consists of 50 parking spaces considered as a baseline to show the difference with previous research methods. AlexNet by Amato et al. [9] required 0.3 seconds to process a single patch and processed only 0.06 frames in 1 second which was slower than the proposed method. The deep CNN method by Valipour et al. [10] required 0.22 seconds to process a single patch and processed only 0.1 frames per second. So, the proposed method performed better in terms of processing speed than

AlexNet by Amato et al. [9] and the Deep CNN method by Valipour et al. [10].

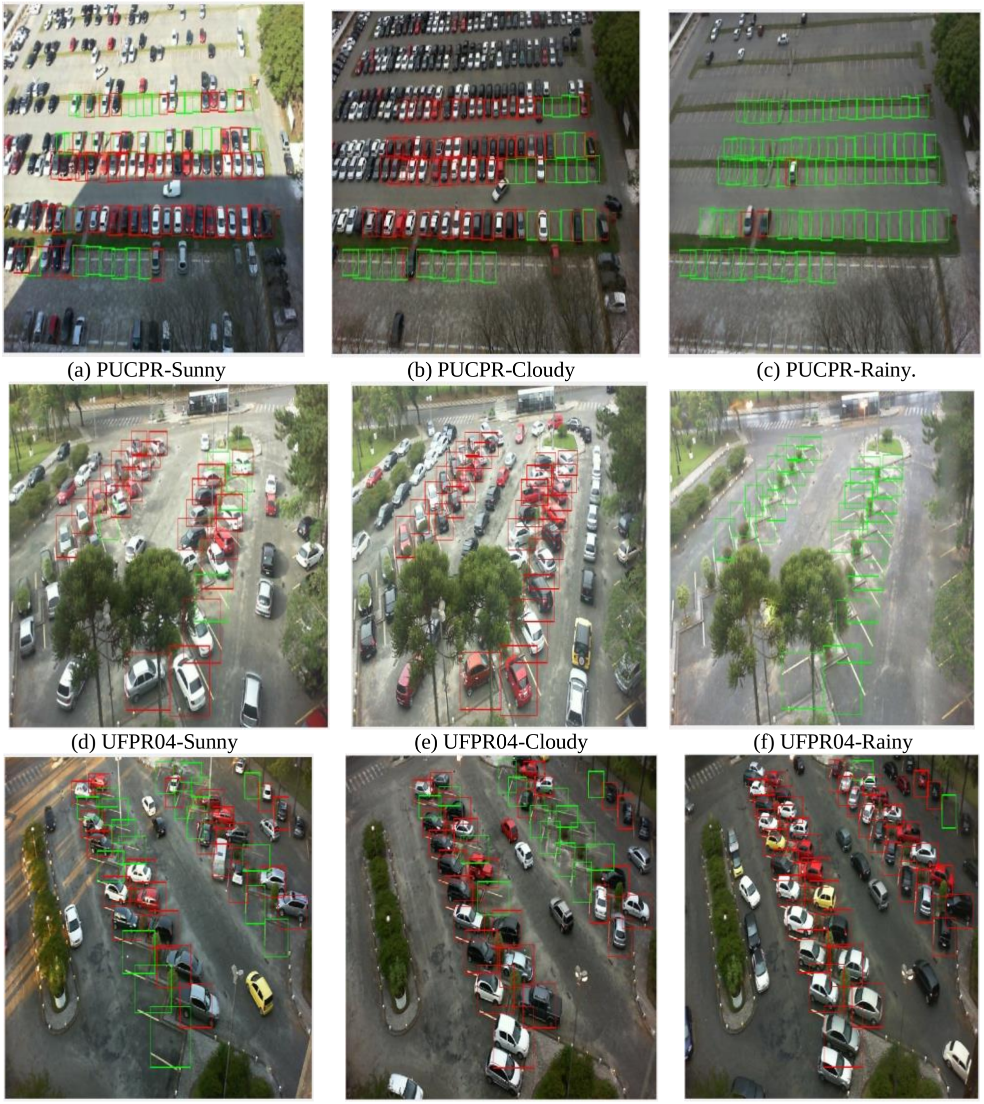
TABLE X. COMPARISON WITH PREVIOUS RESEARCH

Methods	Accuracy	Error	Precision Rate	Recall Rate
Proposed Method	99.47	0.8	99.15	98.83
PKLot[7]	91.52 (averaged) 99.5 (UFPR05)	0.7 (UFPR05)	99.36 (UFPR05)	98.8 (UFPR05)
CarNet[8]	97.04	-	-	-
AlexNet[9]	96.74	-	-	-
Deep CNN [10]	Accuracy Not provided AUC is (0.9994)	-	-	-

Fig. 7(a), Fig. 7 (b), and Fig. 7(c) are the sample output for PUCPR sunny, cloudy, and rainy weather conditions where for each image 100 parking spaces are considered for classification. Fig. 7(d), Fig. 7(e), and Fig. 7(f) are the output for FPR04 sunny, cloudy, and rainy weather conditions where for each image 28 parking spaces are used. Fig. 7 (g), Fig. 7(h) and Fig. 7(i) are the output for FPR05 sunny, cloudy, and rainy weather conditions where for each image 40 parking spaces are used for vacant parking space detection. The output result marks the occupied parking space with red rectangles and unoccupied spaces with green rectangles.

TABLE XI. COMPARISON WITH PREVIOUS RESEARCH IN TERMS OF PROCESSING SPEED

Methods	Processing Time in Seconds Per patch	Processing Speed in Frame Per Second (A frame of 50 patches)
Proposed Method	0.15	1.048
PKLot [7]	Not specified	Not specified
CarNet [8]	Not specified	Not specified
AlexNet [9]	0.3	0.06
Deep CNN [10]	0.22	0.1



(a) PUCPR-Sunny (b) PUCPR-Cloudy (c) PUCPR-Rainy.

(d) UFPR04-Sunny (e) UFPR04-Cloudy (f) UFPR04-Rainy

(g) UFPR05-Sunny (h) UFPR05-Cloudy (i) UFPR05-Rainy

Fig. 7. Out of detected vacant parking spaces.

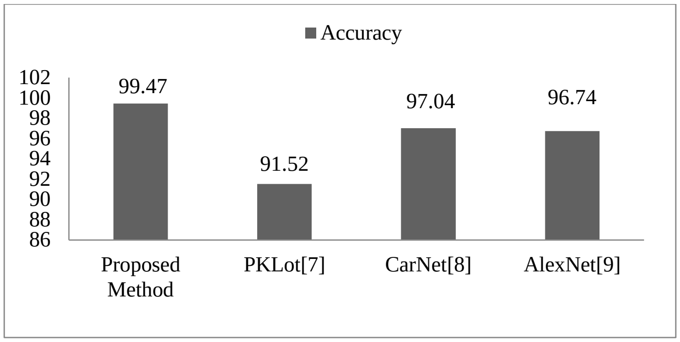
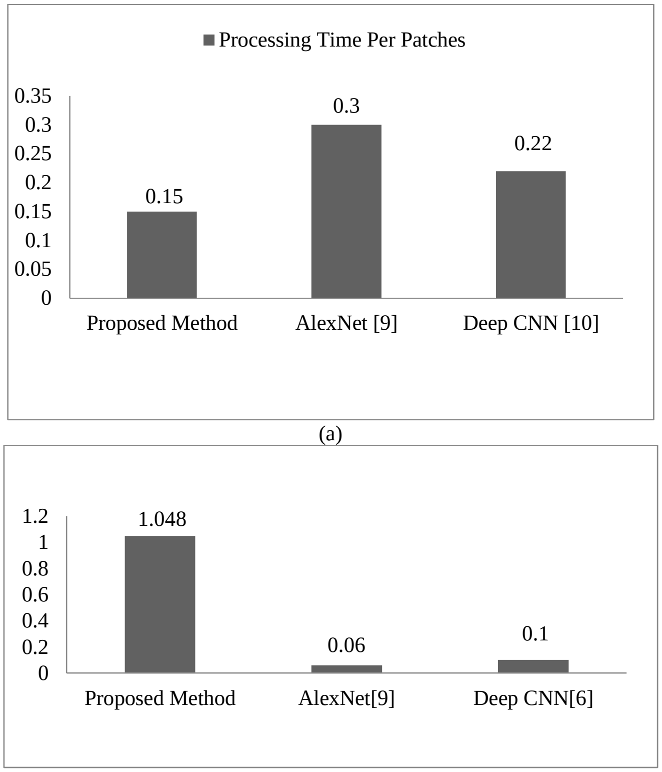


Fig. 8. Accuracy of the proposed method and previous research methods.

The proposed method achieved higher accuracy compared with previous research shown in Fig. 8 due to the usage of features for training, i.e., Contrast, Correlation, Energy, Homogeneity, and Color descriptors such as red, green, and blue channels. In addition, the proposed method also implicates the squared inverse of the distance as a weight to make the classes more separable while training.



(a)

(b)

Fig. 9. (a) And (b) Processing time comparison with previous research.

Proposed methods required less processing time per patch than previous research methods like AlexNet by Amato et al. [9] and the Deep CNN method by Valipour et al. [10] shown in Fig. 9(a). Besides, the proposed method processed more frames per second than AlexNet by Amato et al. [5] and the Deep CNN method by Valipour et al. [10] where each research method considered processing frames of 50 parking spaces shown in Fig. 9(b). The proposed method extracted features from a patch to predict whereas Amato et al. [9] and Valipour et al. [10] used a convolutional neural network and the whole patch needed to be convolved in each convolution of the neural network which required more time than the proposed method.

The proposed method shows robustness in terms of classifying unseen data. According to the validation results, having enough training data proposed method is expected to be capable to work in newer parking areas. Besides, the proposed method is lightweight and can easily be deployed on the server-side or a single Raspberry Pi 3 or Raspberry Pi 4 can be used to run in real-time implication.

V. Conclusion

This research proposes a hybrid method to detect vacant parking spaces using texture-based features and color descriptors. Features are calculated from gray-level co-occurrence matrix and RGB color descriptors to distinguish between occupied and unoccupied spaces. The proposed method illustrated efficiency in terms of accuracy, processing speed, and other performance metrics. Proposed model archived above average accuracy of 99% including validation with unseen data. Experimentation was done on one of the benchmarking datasets named PKLot parking image dataset which contains images of three different parking areas and for each subset images were taken on three different weather conditions at different times of the day. For a desired parking area, the proposed method can be used to provide prior knowledge of the available parking spaces, and vehicle drivers are expected to be able to locate the parking space efficiently. Besides, the proposed method is expected to decrease traffic load and air pollution. Another use case of the proposed method is to detect illegal parking which will be investigated in the future. In addition, an investigation will be done to implicate the proposed method at night and optimize it to work concurrently for both day and night conditions.

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SkySculptor: Intuitive Drone Control Through Ground-Integrated Radar and Foot Gestures in Smart Indoor Environments

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***Abstract*—SkySculptor is a software application designed to optimize drone control in smart indoor environments. The primary focus is on using gesture input for drone control, particularly investigating mid-air free-foot interactions detected by radar sensing. This software application simplifies the process of controlling drones in smart indoor environments. Additionally, outcomes of utilizing a 15-antenna ultra-wideband 3D radar are presented, establishing a dictionary of six directional swipe gestures for controlling drone functions. Based on the findings of this research article, guidelines for the future development of software applications for drone control in intelligent indoor environments are proposed.**

***Keywords*—Drone control; gesture input; ultra-wideband radar; software application; smart environments**

I. Introduction

Efficient, fluid, and expressive interactions that take advantage of body position and movement can be achieved by integrating radar gestures into smart indoor environments. This involves recognizing body position and movement and employing taxonomies to incorporate radar sensing technology [1]. This integration facilitates various interactions, including controlling smart TVs [2], utilizing wearable devices for gesture detection [3], and drone interactions [4]. Airborne gestures can also interact with content displayed on ambient screens [5], while foot movements offer additional avenues for interaction, covering both natural and unnatural gestures [6], [7]. Symbolic touch gestures commonly used on mobile devices can also be incorporated [8].

Recognizing user gestures involves a combination of hardware devices such as accelerometers embedded in smart devices like smart rings [3], [9], [10], various recognition algorithms (e.g., KNN, Random Forests, Convolutional Neural Networks, DTW) and data sets establishing correlations between gestures and system functions. Radar devices such as Google Soli, Walabot, and Sense2Go exemplify non-contact gesture sensors that offer new interaction possibilities with smart environments. Furthermore, attaching a radar device to a drone enables the control of various objects in a smart indoor environment [11]. Radar-detected gestures can range from basic presence and proximity detection to multitouch gestures or foot-based gestures [12], [13], [6]. Studies on radar device interactions suggest various sets of gestures, some focusing on hand gestures [14], [15] while others advocate interactions that involve the whole body [16]. These examples highlight that radar device interactions typically involve the upper body, as detailed by Șiean *et al.* [1]. Despite these advances, the lower part of the body was overlooked in interaction with radar devices.

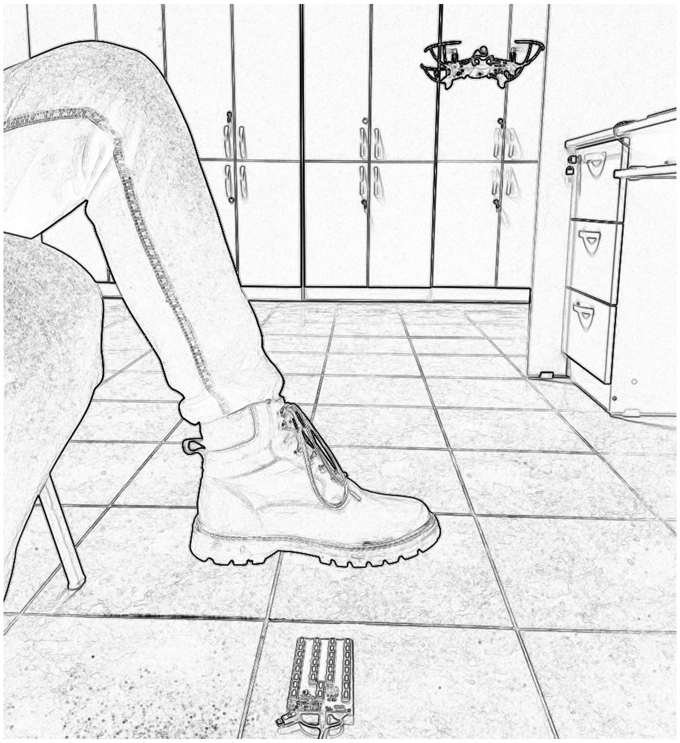


Fig. 1. The walabot radar device, used in SkySculptor, is shown alongside the parrot mambo drone and interaction modes.

In our contribution, emphasis was placed on the following aspects:

1) Software design requirements were defined and incorporated into the design of an interactive system that enables drone control using a radar device integrated, attach, or placed on the floor of a smart environment.
2) A set of six radar gestures executed with the foot was proposed, each associated with specific commands for drone control.
3) An implementation of the software application using a radar with a 15-antenna ultra-wideband 3D radar.

II. Related Work

Gesture-based drone control and radar-based gesture sensing and recognition will be our focus.

A. Gesture-based Drone Control

Research on gesture-based human-drone interaction has explored various approaches [17], [18]. Gestures serve as an effective means of conveying emotions, thoughts, and nonverbal communication, and hand gestures are widely accepted as intuitive communication methods [19]. Controlling drones through hand gestures offers simplicity and intuitiveness. Past studies have investigated hand gesture recognition using vision-based sensors such as RGB and depth cameras, as well as Microsoft Kinect sensors [20]. However, recent developments in safe-to-touch drones have spurred interest in novel forms of interaction, including direct touch and manipulation. For example, HoverBall is a ball-shaped quadcopter capable of sports or game applications [21]. Drones have also been used as haptic feedback devices in virtual reality scenarios [22]. However, these systems face limitations related to environmental factors such as light conditions, viewing angles, and spatial positioning.

B. Radar-based Gesture Sensing and Recognition

The core of radar detection lies in the use of electromagnetic waves. When these waves strike a target, a portion of the signal reflects back to the radar source and the receiver captures the signals. The characteristics of the received signal, such as frequency, amplitude, and delay time, provide information about the detected object, including its shape, orientation, distance, and speed relative to the radar. Radars are advantageous for human detection (e.g. gestures, posts, movement, etc.) as they operate under conditions of high illumination, low lighting, or darkness, when obstructed by surfaces or objects [23], [24], or during different weather conditions [25]. Previous research has presented and evaluated multiple techniques to recognize radar gestures. For example, Gigie *et al.* [14] showcase a case study of data explosion for radar-based human gesture detection. They introduced a simulation framework based on a physical model to generate radar signals corresponding to various human gestures. With the availability of Google Soli in the mobile ecosystem, Leiva *et al.* [26] devised a hybrid CNN+LSTM deep learning model. They conducted a comprehensive study exploring the performance of mid-air gesture recognition while covering the radar sensor with three distinct fabrics (leather, wool, and cotton). The model demonstrated an exceptional average performance accuracy of 95%, AUC of 99%; RadarNet [27] utilizes an effective recognition approach for radar gestures, utilizing a Convolutional Neural Network. It operates efficiently on processors with limited computational capabilities. On the other hand, mHomeGes [28] is a system designed to detect radar gestures with an accuracy of 95%, particularly designed for smart home interactions. Therefore, we propose a radar sensor-based gesture recognition system for drone control that extends body gestures using *foot* gestures.

III. Design Requirements for SkySculptor

By analyzing the relevant scientific literature and considering the potential application domain, which focuses on the interaction between drones and gesture-based foot movements in smart indoor environments using integrated, attached or floor-placed radar devices, we can establish the necessary design requirements for SkySculptor as shown in Fig. 1. Next, the design criteria for the development of the SkySculptor software application.

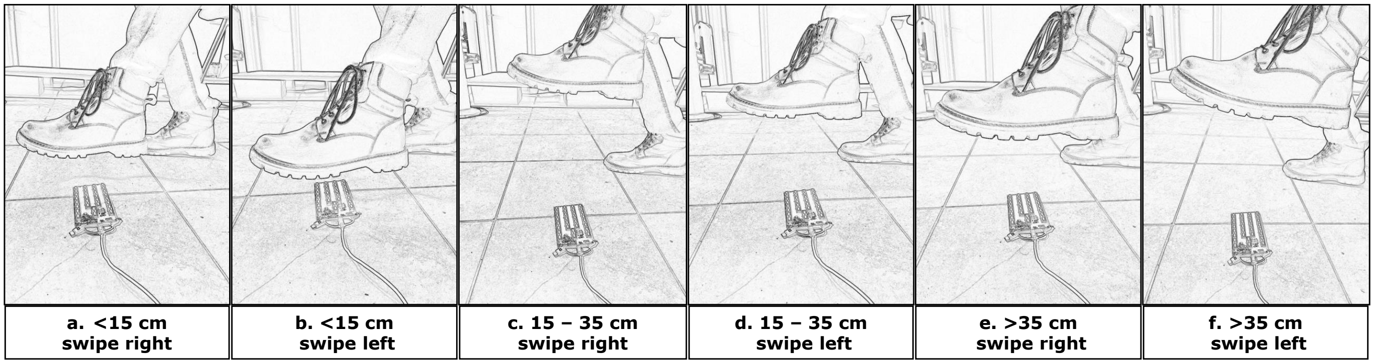
(a) *Open source technology:* SkySculptor strongly emphasizes the adoption of open technologies to promote the development and progress of innovative specialized software applications designed for users who operate drones in smart indoor environments. This guiding principle also applies to SkySculptor, which features a fully developed software application created using open technologies. The goal of this system is to encourage research and support the ongoing advancement of drone interactions in intelligent indoor environments through the use of radar gestures.

(b) *Smart spaces orientation:* Accurate positioning of the radar device in the recommended locations, as proposed by Şiean *et al.* [1], enables effective handling of complex gestural interactions between users. Similarly, for interactions between drones and physical objects, the approach suggested by [2] can be applied. This approach is seamlessly integrated into the software application SkySculptor, with a particular emphasis on the areas of the floor and the interaction facilitated by the movements of the feet.

(c) *Easily integrate, attach, or place the radar sensor on objects or devices:* Traditionally, drone control has been done using joysticks or smartphones. However, in our scenario, we propose a shift towards using an integrated radar device that can be attached to or placed on the floor for drone interaction. Radar devices have unique features that allow them to integrate seamlessly into various objects or be attached by users, providing researchers with the opportunity to propose innovative methods of interaction. The SkySculptor software application places an emphasis on integrating the radar device in the floor and facilitating interaction with the feet. This is motivated by the lack of gestures involving the lower body, despite the numerous proposals for interaction focused on the upper body, as discussed by Şiean *et al.* [1]. By prioritizing the integration of the radar device into the floor and enabling interaction based on leg movements, we aim to enrich and diversify gestures and interactions in intelligent indoor environments within the context of HDI.

Requirement (c) can be satisfied by utilizing the principles that govern the functioning of radar devices and their ability to detect objects. This requirement provides various options for the installation of the radar device, allowing interaction with the drone. At the same time, it addresses the challenges associated with gesture recognition that may arise due to low light or unfavorable weather conditions. When open technology is employed in the development of a software application, it becomes easier to extend and improve its functionality. As a result, a new requirement is introduced for SkySculptor, which specifically describes the ease of its development.

(d) *Python-orientation:* Devices that are capable of running



a. <15 cm swipe right

b. <15 cm swipe left

c. 15 – 35 cm swipe right

d. 15 – 35 cm swipe left

e. >35 cm swipe right

f. >35 cm swipe left

Fig. 2. Various mid-air gestures combining directional swipes and distance from the sensor enable control of drone functions.

SkySculptor are those that have a Python interpreter and are equipped with a USB port for connecting the radar device.

Software applications developed using the Python framework are well known for their fast and reliable performance. This decision was made to ensure that the tools are compatible with various devices that have a Python interpreter, providing a consistent experience for users. Using Python[1], the process of integrating drone and radar device SDKs became easy, making it easier to connect to these devices. Using the drone SDK[2] and establishing a connection to the radar device, we successfully incorporated the necessary functionality to control the drone without any difficulty.

IV. Implementation Approach and Prototype

We propose a gesture recognition system to control drones using radar sensors. The system focuses on using foot gestures for control. To evaluate the technical feasibility of this radar sensor-based gesture recognition system for drone control, taking into account the availability and affordability of radar technology on the market, a prototype SkySculptor was developed using the 15-antenna Walabot Creator device and the Walabot API.[3] The Mambo Parrot drone was used in conjunction with the prototype. The trajectory of the detected target above the radar was captured and expressed as x, y, and z coordinates. Two directional swipe gestures (referred to as *swipe left* and *swipe right*) along the y axis. Furthermore, the distance from the sensor on the z axis at which these gestures were made was used to define three active zones (*near*, *close*, and *far*) above the radar. Fig. 2 shows visual representation of the gesture set. When the two directions and three zones were combined, a total of six gestures were obtained. These gestures can be assigned to three types of functions commonly used in drone control: *take-off/land* for initiating or ending the flight of the drone, *start/stop video* for controlling the camera, such as taking photos or starting/stopping video recording, and *forward/backward* for moving the drone in the forward or backward direction. This method is the same as the paper [2].

We conducted a preliminary evaluation of our application by performing foot gestures that corresponded to various scenarios, including take-off, landing, starting and stopping video recording, moving forward, and moving backward a drone. A visual representation of these gestures can be seen in Fig. 2. If additional gestures are required, modifications to our basic gesture recognition pipeline may be necessary, such as preprocessing the raw signal or implementing new recognition techniques [29]. Fig. 3 displays $\theta-R$ images obtained from the Walabot radar when placed on the floor and corresponding to the gestures shown in Fig. 2, with varying distances measured by the radar sensor.

The Walabot radar sensor was placed on the floor at various locations to generate the heatmap screenshot for different scenarios. This placement was chosen to allow for interaction with the feet. In each scenario, the experimenter sat on a chair and used his right foot to perform gestures (a) and (b) within the active zone labeled *near*. For scenarios (c) and (d), a mouse pad was placed on the floor with the Walabot radar sensor underneath. To represent the situation in which the radar sensor is placed below an object such as a carpet, the experimenter raised his foot higher on the z axis and made gestures for the active zone labeled *close*. In the last case, the radar sensor was placed on a vibrotactile floor, which is available in our research laboratory. The experimenter executed gestures (e) and (f) to simulate the scenario in which the sensor is integrated into the floor within the active zone labeled *far*. This method is the same as the paper [2].

Another assessment was made when the experimenter was seated, allowing interaction through knee gestures. By sliding the knee to the left and right at varying distances from the radar sensor, the experimenter could access three active areas: *near, close,* and *far* for interacting with drone. The Walabot radar device was placed on the wall, 20 cm above the floor. Alternatively, when the experimenter was not seated, more extensive sliding movements of the left or right foot could be performed to execute foot gestures. Fig. 3 illustrates foot gestures, the distance measured by the radar sensor, and the different placements of the sensors. For more examples of where to place radars, we recommend looking at [1].

Different types of data can be extracted from a radar system, such as velocity, range, and direction of motion. The specific details obtained vary depending on the modulation technique utilized to control the drone, for example:

[1] The Python programming language is widely recognized as one of the most popular programming languages. It consistently holds the top position in the Tiobe ranking (https://www.tiobe.com/tiobe-index/), with a steady rating of 13.97% from 2023 to 2024.

[2] https://developer.parrot.com/docs/index.html

[3] https://api.walabot.com/_sample.html

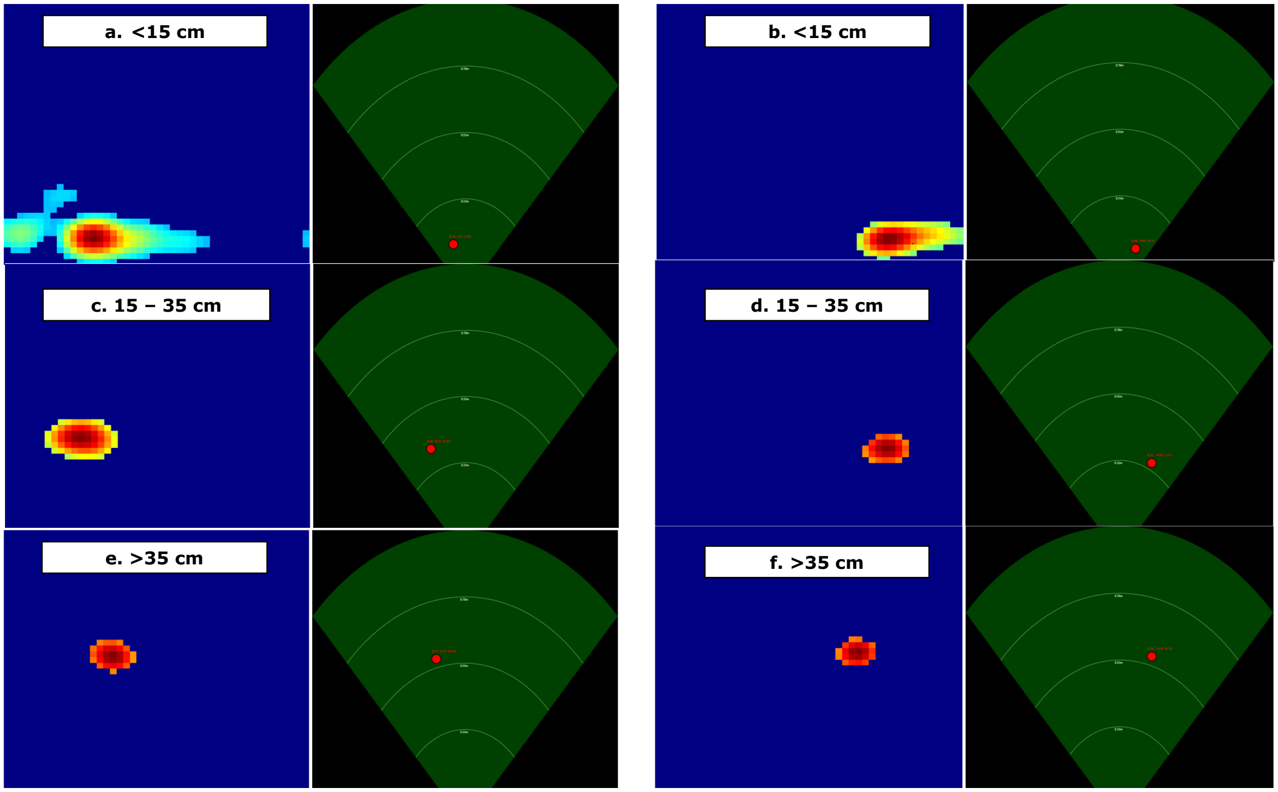


Fig. 3. The radar sensor captures $\theta - R$ images of various actions, including (a) take-off, (b) landing, (c) starting and (d) stopping video recording, (e) moving forward, and (f) moving backward. Each image shows foot gestures and the distance measured by the radar sensor.

- 1D, *continuous-wave (CW)* — modulation separates objects by their velocity. There is no possibility of distinguishing objects of similar velocity from objects' location. Frequently used for motion detection applications. Drones have the potential to be used in various sports, including running [30]. In addition, a 1D radar system can be used to indicate the moment when a runner crosses the finish line.
- 2D, *frequency-shift keying (FSK)* — modulation separates objects by distance and velocity. Location of objects in a one-dimensional environment without information about the angle. The modulation being FSK, it only separates objects based on speed, and it offers the advantage of measuring the distance. Drones, for example, are found on construction sites before or during the execution of construction work, working alongside human workers [31]. The 2D radar will be utilized to gauge the distance between objects.
- 3D, *frequency-modulated continuous wave (FMCW)* — multiple input/multiple output (MIMO) modulation separates objects by velocity, distance and angle. Objects of the same speed, distance, and angular position can be detected and their 2D location determined. Multiple transmission and reception antennas increase the resolution of the sensor. Drones have various applications in emergency situations, such as search and rescue operations [32]. In the event of an avalanche, a 3D radar sensor can be used to determine the distance between the rescuers and the individuals in need of assistance.
- 4D, *FMCW MIMO* — modulation separates objects by velocity, distance and angle (horizontal and vertical). Objects with the same speed, distance, and angular distance can be detected. Objects can be located in 3D. Compared to a 3D radar, 4D radars use more antennas and can detect the angle between horizontal and vertical. This brings about the advantage of locating objects in a 3D environment. Drones or clusters of drones are commonly used for aerial shows [33], as well as for image projection [34] and aiding in projections [35]. The 4D radar sensor can be used to calculate the speed of the aerial displays to coordinate their positions.

We did not use the 1D-RADAR and 2D-RADAR categories because we want to cover as many functionalities SkySculptor as possible and, in certain situations, distinguish gestures from different objects in the room. Depending on the resolution, we can choose different commercial radar sensors, also putting emphasis on the operating distance. For example, in the case of integrating the radar sensor into the floor or wall, we are going to need a much smaller distance, compared to the situation where the sensor is integrated ceil. The initial form of the algorithm scans targets to flip pages of an opened document; If the y coordinates of the identified targets were decreasing, the up button was pressed to access the previous page, and if the targets were increasing, the down button was pressed to access the next page. We modified this algorithm at both the recognition level and the semantic level of gestures. We wanted to better recognize the original form, so we calculated the sum of the evaluated y coordinates. Now, if the values are decreasing and the sum is negative, we stand for a *swipe-left*; otherwise, if the values are increasing and the sum is positive, a *swipe-right* is identified. For each identified gesture, we send a specific command via WebSocket to the Drone running on the PC in our situation, such as: forward [36], [37], backward [38], [39], take a photo [11], etc.

Radar-sensing gestures imply that a gesture is made in air, without touch. To this end, another feature that is interesting for a gesture is the distance of foot from the Walabot. In this way, we modified the original algorithm by also capturing the z coordinate. Because a gesture is made up of a set of points, we calculate the average distance between the foot and Walabot. We obtain the result that a gesture can be performed near *near* Walabot, at a reasonable distance from it *close* or very far from Walabot *far*. In summary, we identified *two* swipe gestures x *3* possible positions of each gesture, that is, a set of *six* gestures.

V. Results

The creation and implementation of SkySculptor, a specialized software designed to improve drone interactions using foot gestures detected by radar, have produced positive results. The software was developed with specific design requirements to ensure smooth compatibility with open-source technologies. Integrating radar sensors into the application's framework enabled drone control by recognizing foot movements detected by the Walabot radar device. A set of six unique directional swipe gestures was introduced, each linked to predefined drone functions, allowing users to easily perform actions like drone take-off/landing, starting/stopping video recording, and changing directions. During the prototype phase, the use of a 15-antenna ultra-wideband 3D radar in combination with the Parrot Mambo drone was used to validate the effectiveness of the gesture recognition system. The ability of the radar sensor to capture detailed foot trajectories at various distances and angles provided reliable data for accurate gesture recognition. Detailed radar heat maps showed the gestures and spatial positions of the radar sensor. Overall, the successful implementation of SkySculptor demonstrates its potential to extend the human-drone interaction in smart indoor environments, paving the way for future advancements in this evolving field.

VI. Discussions

The introduction of SkySculptor, a software application aimed at simplifying drone control through radar-based foot gestures in intelligent indoor spaces, involves a series of discussions. The central theme of this scientific article revolves around the effective merging of open-source technologies with the intricacies of smart indoor environments to ensure a variety of user interaction methods and technological functionalities. Using radar sensors, SkySculptor uses conventional drone control techniques, offering users an intuitive interface based on foot gestures, which improves the accessibility of indoor drone manipulation. Moreover, the successful deployment and verification of SkySculptor underscore the potential to extend radar-based gesture recognition systems to transform the dynamics of human-drone interactions. These outcomes collectively pave the way for a wider acceptance of radar-based foot gesture control systems.

VII. Limitations and Future Work

Our implementation uses Python-based APIs to control drones and radar devices. While Python's versatility and widespread support are commendable, certain specialized or restricted environments may encounter difficulties in fully accommodating Python. This is particularly true for wearable devices or embedded systems, which may have limited resources or be optimized for alternative programming languages. Another limitation is associated with the data transmission capacity of the radar device. Enhancing this capability could enable for a more extensive implementation of a wider range of gestures for drone control. Currently, the SkySculptor software tool does not have a predefined set of user-customized gestures. Future development considerations include improving the gesture dictionary through code generation and incorporating a radar device capable of processing larger volumes of data. Lastly, there is a limitation in terms of drone compatibility, which is currently limited to Parrot drones. Adapting the software implementation to be compatible with other drone brands presents a challenge. In addition, limitations extend to factors such as drone size, flight time, and sensor configurations. These challenges present opportunities for further development within the SkySculptor software system. Furthermore, different types of radar will produce different types of data. Therefore, it is useful to investigate other characteristics of radar sensors, such as resolution or field of view, in future work to implement various designs of gestures. We leave the examination of diverse radar technologies for future research.

VIII. Conclusion

The software application, SkySculptor, presents a novel approach to controlling drones in smart indoor environments by using gestures of the foot on radar. This addresses a gap in the current literature regarding the use of foot gestures for drone control. The article provides an overview of the context and scope of SkySculptor, emphasizing the fundamental principles of radar sensing and the potential of this technology for controlling drones in intelligent indoor environments. The related work highlights the limited information available on foot gestures for drone control despite previous research efforts. Additionally, the paper presents a detailed workflow for SkySculptor, which includes design requirements, an implementation approach, and a prototype of the proposed system.

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Declarations

The authors declare no conflict of interest. Data sharing is not applicable to this article, as no data sets were generated or analyzed during the current scientific paper.

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Classifying Motorcycle Rider Helmet on a Low Light Video Scene using Deep Learning

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***Abstract*—For safety in transportation, it is important to always monitor the use of proper motorcycle helmet, especially at night. One way to enforce transportation rules and regulations in wearing proper motorcycle helmet is to use computer vision technology. This study focusses on classifying motorcycle rider helmet at low light video conditions, like at dusk and at night, using YOLOv5 and YOLOv7 with Deep SORT. In these deep learning methods, the study tunes and optimizes hyperparameters to attain high accuracy in classifying motorcycle rider helmet at this challenging environment. To accomplish this objective, a vast and diverse dataset was employed, containing classes such as riders, different types of helmets (valid and invalid), and instances of riders not wearing helmets at all in Metro Manila, Philippines. The results show that Hyperparameter 3 consistently outperformed other settings in terms of precision (95.6%), recall (91.2%), and mean average precision (mAP) scores across multiple scales and time frames with 95.1% on mAP@0.5 and 76.3% on mAP@0.95, owing to greater epochs, quicker learning rates, and lower batch sizes.**

Keywords*—Artificial intelligence; computer vision; computer vision problems; object detection; YOLOv5; YOLOv7; Deep SORT; deep learning

I. Introduction

Wearing motorcycle helmets is essential for the safety of riders especially in the Philippines, where over 1,000 motorcycle-related road crashes occurred in 2019 [1-2]. Research from the World Health Organization reveals helmets can reduce motorcycle crash death risk by up to 40% [3]. This emphasizes the necessity of helmets to prevent injury or death for riders [4-8]. Helmet use is mandated by many countries' laws. Yet, detecting helmet use in low-light conditions, at dusk or at night, remains a challenge. This study evaluates You Only Look Once (YOLO) version five models combined with Deep Simple Online Realtime Tracking (Deep SORT) for detecting helmet use in nighttime traffic situations in Metro Manila, Philippines. Meanwhile, Metro Manila's traffic persist due to car-centric policies and resistance to eco-friendly transportation [9]. Efforts like the Public Utility Vehicle Modernization Program face challenges due to historical norms and current crises. Addressing low light conditions in object detection is another hurdle, tackled by a study that integrates multi-scale detection, attention mechanisms, and Convolutional Block Attention Module (CBAM) for improved accuracy in identifying objects under limited light [10]. The YOLOv5 Small – Feature Combinatorial Grouping (FCG) model showcased up to 87.5% mean accuracy precision (mAP) in detecting objects like helmets in challenging low light, highlighting the potential of advanced techniques.

Combining YOLOv7 and Deep SORT offers cutting-edge object recognition and tracking, applied in real-time video analysis [11]. They contribute to safer roads by identifying helmetless riders. These open-source technologies continually evolve, serving the research community and the public. The YOLOv5 algorithm achieves high detection accuracy while maintaining real-time performance, making it suitable for a variety of computer vision applications. On the other hand, YOLOv7 is a one-stage object detection system that divides an image into grid cells and predicts bounding boxes and class labels for each. Both algorithms utilize a convolutional neural network (CNN), mainly employed for calculating bounding boxes, and the use of a SoftMax layer for class label prediction [12]. The architecture of the network consists of three main parts: the backbone network, the neck network, and the head network. The backbone network oversees extracting picture features. The neck network oversees fusing the backbone network's extracted features. The head network oversees predicting the bounding boxes and class labels for the objects in the dataset.

Moreover, the main contribution of this study is the tuning and optimization of hyperparameters within the framework of YOLOv5 and YOLOv7 with Deep SORT to classify accurately motorcycle helmets at low light video scenarios with respect to the authors' previously conducted study [13]. To the best of our knowledge, we believe that this is the first study done on this type of video scenes for this application. The enhancements made will definitely be beneficial to the implementation of transportation rules and regulation on wearing of proper motorcycle helmets at all times using computer vision technology.

II. Related Works

A. YOLOv5

YOLOv5 is an object detection technique that improves on the success of prior YOLO models by introducing a real-time object detection methodology. It performs object detection tasks by dividing an input image into grid cells and predicting bounding boxes and class probabilities for items within each grid cell using a deep CNN architecture [14]. Its methodology includes a novel approach known as a "cross-stage partial network" that improves the network's feature representation capabilities and enables more accurate object detection [12]. The algorithm achieves high detection accuracy while maintaining real-time performance, making it suitable for a variety of computer vision applications. In a study conducted by Jia et al. (2021) [15], they proposed an end-to-end motorcycle helmet detection using YOLOv5 wherein motorcycle riders were detected including the riders wearing helmets. The model was able to achieve an exceptional accuracy having an mAP up to 97% for each classes. However, it is important to note that these results were only evaluated in a high-light condition since the dataset used only contains noon time footages of highways.

B. YOLOv7

YOLOv7 is an improvement of YOLOv5. It is also a one-stage object detection system that divides an image into grid cells and predicts bounding boxes and class labels for each. It also uses a CNN which primarily used to forecast the bounding boxes, and a SoftMax layer is used to predict the class labels [10]. Its network is divided into three sections: the backbone network, the neck network, and the head network. The backbone network oversees extracting picture features. The neck network oversees fusing the backbone network's extracted features. The head network oversees predicting the bounding boxes and class labels for the objects in the dataset. As for the backbone network in YOLOv7, it uses the CSPDarknet53 network [16–19]. CSPDarknet53 is a revision of the Darknet53 network that has been shown to improve performance and accuracy. In YOLOv7, the neck network is the called the YOLOv7-Neck network, which is used in fusing the features extracted by the backbone network. The head network, on the other hand, is in charge of predicting the bounding boxes and class labels for the image's objects. It is trained using a dataset of tagged images with bounding boxes and class labels for the objects in the images. The training procedure is divided into two stages: pre-training and fine-tuning. Moreover, the network is trained on a huge dataset of photos tagged with bounding boxes and class labels for the objects in the images during the pre-training phase. The pre-training phase is used to understand the fundamental properties of objects.

According to Nandhakumar [19], YOLOv7 outperforms earlier object detection algorithms in terms of both speed and accuracy. It can reach real-time speeds of up to 160 frames per second while maintaining great precision. As a result, it is a helpful tool for a wide range of applications, including autonomous driving, video surveillance, and robots. Currently, there have been no studies yet that utilized YOLOv7 in detecting motorcycle helmet specifically in low-light conditions. It has been used before in detecting Camellia Oleifera Fruit in orchard scenes by Wu et al [20], as well as Chicory Plant by Gallo et al. [21]

C. Deep SORT

Deep SORT on the other hand is a method for tracking multiple objects that combines a deep learning-based object detector and the SORT (Simple Online and Realtime Tracking) algorithm. This method improves on traditional tracking methods by employing a deep neural network to generate high-quality embeddings that encode the appearance of seen objects [19-20]. These embeddings are then used in conjunction with a Kalman filter-based tracking framework to associate and track objects over successive frames. Deep SORT provides powerful and dependable tracking by combining appearance, motion dynamics, and temporal information. social distancing measures during the COVID 19 pandemic by Narinder Singh Punn et al. (2020) [22], as well as Pear fruit detection by Addie Ira Borja Parico and Tofael Ahmed (2021) [23].

D. Scale

YOLO has multiple scales, from nano, small, medium, large, xlarge. The nano-scale model is the algorithm's smallest and fastest variant, but least in precision. It contains fewer layers and characteristics than the medium and large scales, making it better suited for deployment on resource-constrained devices. The YOLOv5 small-scale model performs effectively in object detection tasks despite its smaller size. It detects objects in an image using a single convolutional neural network (CNN) architecture, with a focus on small objects, and incorporates data from several sizes of the input image using a feature pyramid network (FPN) [11].

A single convolutional neural network (CNN) architecture is used in the medium-scale model to detect objects. It also anticipates object-bounding boxes through the use of anchor boxes [26]. It does, however, use more anchor boxes than the small-scale model, allowing it to distinguish objects with more precision. It can also detect objects with high precision while maintaining real-time performance as its major characteristic, making it suited for a wide range of real-world applications. Finally, the large-scale model operates similarly to the previous model scales, but because it employs larger layers and a greater number of anchor boxes than the small and medium-scale models, it allows for the identification of objects with even greater precision [14].

E. Inference

To use model testing and inference in YOLOv5, which is the process of using the trained model to make predictions based on new unseen data. The model would be prepared and configured the Python environment with the required dependencies. Then all the test images or videos should be collected to generate the YOLOv5 configuration file, this includes the model's weights and parameters. Then infer by running the test data through the model and generate bounding box predictions for object recognition. The predictions can still be refined by removing redundant detections with non-maximum suppression and scaling the coordinates to fit the original image size. Finally, plot the bounding boxes on the images or videos to visualize the results [1][16].

F. Hyperparameters

In YOLO, adjusting hyperparameters entails fine-tuning several settings to optimize the model's performance. Considering the speed and accuracy requirements, the architecture of the YOLOv5 model can also be adjusted by selecting different scales such as YOLOv5s, YOLOv5m, or YOLOv5l [27]. Experimentation with hyperparameters such as learning rate, weight decay, and batch size, can all have a major impact on training. To boost generalization, regularization techniques such as dropout and data augmentation can be used. It is critical to evaluate the model's performance using evaluation metrics such as mean average precision (mAP) and to iteratively alter the hyperparameters based on the results. By carefully tweaking these hyperparameters, the model's detection accuracy and overall performance can be enhanced [18]. Full model framework can reference based on the image below Fig. 1, the application of Kalman filter in which Deep SORT is integrated for optimization [24] [28].

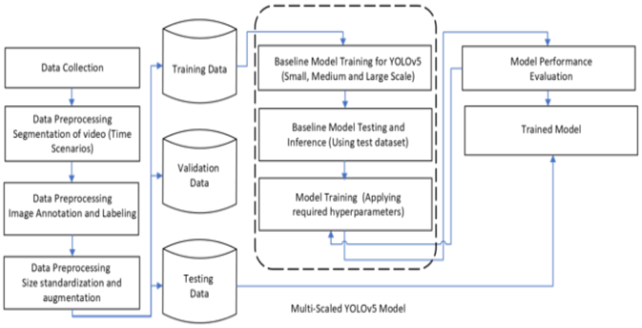
Data Collection
Data Preprocessing Segmentation of video (Time Scenarios)
Data Preprocessing Image Annotation and Labeling
Data Preprocessing Size standardization and augmentation
Training Data
Validation Data
Testing Data
Baseline Model Training for YOLOv5 (Small, Medium and Large Scale)
Baseline Model Testing and Inference (Using test dataset)
Model Training (Applying required hyperparameters)
Model Performance Evaluation
Trained Model
Multi-Scaled YOLOv5 Model

Fig. 1. YOLOv5 multi-scaled conceptual framework.

Deep SORT is a deep learning-based multi-object tracking algorithm that is capable of tracking objects over time even when they are occluded or partially visible. It uses a combination of appearance information and motion cues to track objects in real-real time. By combining the YOLOv7 with Deep sort, the system works by first using YOLOv7 to detect objects in each frame of a video stream. The detected objects are then passed to the Deep Sort algorithm, which associates objects across frames and tracks them over time. By combining both object detectors, the system can track multiple objects in real time, even in complex and cluttered scenes.

It is critical to apply Kalman filter in improving Deep Sort algorithm's tracking performance as it adds temporal information and refine tracking predictions. The Kalman filter is initially initialized with the object's position and velocity represented by the state vector and covariance matrix, then forecasts the next state based on the object's motion model throughout each time step. When new detection or tracking data becomes available, the Kalman filter updates the measurement, including the measurements into the estimating process and changing the state estimate. This enables the Kalman filter to smooth out noisy detections, handle occlusions, and provide more accurate and consistent object tracking predictions in Deep SORT [24]. The full model framework can be referred to using the graphic below Fig. 2.

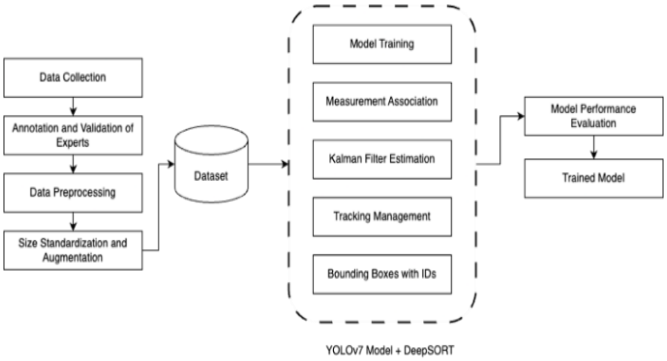

Fig. 2. YOLOv7 + Deep SORT conceptual framework.

G. Synthesis

Reviewed studies indicate that the performance of YOLOv5 is limited in low-light conditions while YOLOv7 remains unexplored along with the implementation of Deep SORT in terms of detecting motorcycle helmets in low-light scenarios. The researchers then aims to address this by exploring the performance of the two models with the help of hyperparameter tuning to achieve optimal results.

III. Methodology

The study compared two YOLO versions: YOLOv5 and YOLOv7. Deep sort was integrated as an optimization in YOLOv7 [24], [25].

A. Scaling

To ensure uniformity in image dimensions and maintain consistency during both the training and inference stages of the model training, each image were resized to a resolution of 640x640 pixels using Roboflow.

B. Inference

The dataset was divided into three parts: 70% for training set, 20% for validation set, and 10% for testing set with the use of Roboflow. After the model has been trained using the training set. The validation set was used to evaluate the performance of the model based on the initial training for the optimization of hyperparameters then the testing set was used to evaluate the unbiased performance of the model on new unseen data.

C. Tuning amd Optimization of Hyperparameters

Three hyperparameter configurations were used: (1) Hyperparameter 1 with 0.01 LR, 64 Batch, and 50 Epochs, (2) Hyperparameter 2 with 0.02 LR, 32 Batch, and 75 Epochs, (3) Hyperparameter 3 with 0.03 LR, 16 Batch, and 100 epochs.

The study also included another version of the YOLO, which is version 7. Most of the initial processes of this model are the same as YOLOv5, but it differs in processes such as measurement association and Kalman Filter Estimation.

D. Data Gathering

The dataset was gathered from a bustling street in Makati City, Philippines, renowned for its substantial motorcycle traffic. The data collection process was strategically conducted during three distinct timeframes to encompass diverse lighting conditions: 5-6 PM, 6-7 PM, and 7-8 PM.

E. Data Pre-Processing

In this step, Smart Video Player was used to monitor the video footage and to identify which timeframes would be relevant to be used in the model. This was followed by annotation. The next step is annotation. The collected footages were monitored to make sure that there were enough types of riders for each scenario: riders with helmets (half-faced or full faced), no helmets, and invalid situations.

The images were then annotated and separated using the training-validation-test splitting method, wherein 70% was used for training, 20% was used for validating, and 10% was used for testing. The images were annotated with four (4) label classes namely Motorcycle Rider, Helmet Full-Faced, Helmet Half-Faced, No Helmet, and Invalid Helmet as shown in Table I.

TABLE I. IMAGE LABEL CLASSES

Class Label	Image Sample
Rider Full Face	
Rider Half-Face	
Rider Helmet Invalid	
Rider No Helmet	

Three strategies were used for pre-processing, including auto-orientation, resizing, and class modification. Images were auto-orientated to align to a standard orientation before feeding them into the model. This technique ensures that the images are in the correct orientation for processing, which can increase the model's accuracy. Because the orientation of the motorcycle rider and helmet might change substantially in different photos, auto-orientation is especially important in the context of helmet recognition for motorcycle riders.

The images were then resized and expanded to the typical size of 640x640. This strategy ensures that all of the photos are of the same size, which is required for the model to efficiently assess the images. Resizing the photos can also help to minimize the model's computational complexity, making it faster and more efficient. In the area of motorcycle helmet recognition, scaling the photos to a consistent size can be very significant because the size of the motorcycle rider and helmet can vary greatly between images.

Finally, the images were class modified by mapping and dropping specific classes from the dataset. In this scenario, 16 classes were mapped while 0 were dropped. This strategy ensures that the model is trained on the relevant classes and can increase the model's accuracy. Dropping classes entails deleting extraneous classes from the dataset whereas mapping classes requires merging comparable classes into a single class. In the domain of motorcycle helmet detection, mapping and removing classes can help to ensure that the model is trained on the necessary classes and can detect helmets effectively.

F. *Data Augmentation*

Various image enhancement techniques were employed to augment the dataset. These included flipping, rotation, cropping, grayscale conversion, and color distortion. Flipping involved horizontal or vertical image flipping, while rotation altered images in clockwise, counterclockwise, or upside-down orientations. Random cropping was applied to zoomed image sections. Grayscale conversion turned images to grayscale, and color distortion adjusted hue, saturation, brightness, and exposure [22]. Applying these enhancements resulted in three training examples per original image, expanding and diversifying the training dataset. These techniques increased the model's resilience to input photo variations.

Bounding box augmentation was also performed, applying the same techniques to helmet-bounding boxes for accurate post-transformation alignment [22]. Augmentation, in the context of motorcycle helmet identification, improved model resilience and accuracy. The augmented, pre-processed dataset was split for model training, validation, and testing. A YOLOv5 model was developed for different scales, with modifications based on three time frames.

The time frames (5-6 PM, 6-7 PM, 7-8 PM) accounted for varying luminance, affecting helmet visibility. Images were tagged into four classes as depicted in Table I, "Rider Full Face" depicted helmets covering the entire head. "Rider Half Face" showed helmets protecting the top and back, excluding the chin. "Other Helmets" encompassed non-motorcycle headgear. "Rider No Helmet" included images of unprotected riders. This approach facilitated effective helmet detection and classification.

G. *Model Training*

The dataset of photos or videos of motorcycles and motorcycle riders wearing helmets was prepared by ensuring the following: bounding boxes were drawn around the objects of interest (motorcycles and helmets), together with class labels indicating whether the object is a motorcycle or a helmet. It is critical to include a diverse range of motorcycle and helmet types in the dataset to guarantee that the model can detect these objects under a variety of situations.

After the dataset has been prepared, the YOLOv5 model architecture must be configured. This entails deciding on a model size (such as YOLOv5s, YOLOv5m, or YOLOv5l) and determining the number of classes to detect. In this particular scenario, the motorcycle and the rider’s helmet.

After configuring the model architecture, the next step is to start the training process. During training, the model iteratively updates its weights based on the loss calculated between the predicted and ground truth bounding boxes and class probabilities. The objective is to minimize this loss function by adjusting selected hyperparameters until the model produces accurate and consistent predictions.

For each of the architecture, time frames were considered to segment changes in lighting conditions. Then, the three hyperparameters were used within the experiment. Aside from using the default hyperparameter setting, additional settings were included by changing the learning rate, batch size, and epoch during training. Learning rate is a hyperparameter that determines the magnitude of the update to the model's parameters during the training process. It controls how quickly the model converges to the optimal solution and can have a significant impact on the model's performance. Batch size refers to the number of training examples used in one iteration of the optimization algorithm during the training process. The batch size is a hyperparameter that can have a significant impact on the model's performance and training time. Lastly, in machine learning, an epoch refers to a complete iteration through the entire training dataset during the training process. The number of epochs is a hyperparameter that determines how many times the algorithm will cycle through the entire dataset. Each epoch is broken down into batches, and the model's parameters are updated based on the loss function calculated on each batch.

To further discuss the optimization process, different hyperparameter settings were applied in the different YOLOv5 architectures (YOLOv5s, YOLOv5m and YOLOv5l) and YOLOv7 as shown in Table II, specifically, the first hyperparameter setting has a configured learning rate of 0.01, batch size of 64, and 50 epochs. The second had a higher learning rate of 0.02, but with a smaller batch size of 32, and more epochs of 75. The third setting has the highest learning rate of 0.03, smaller batch size of 16, and more epochs of 100. Though these settings, and applied in the different time frames, optimized HP can be determined for each of the architectures.

TABLE II. TRAINING HYPERPARAMETERS

Hyperparameter Name	Learning Rate	Batch Size	# of Epochs
H1	0.01	64	50
H2	0.02	32	75
H3	0.03	16	100

Moreover, to improve the robustness of the model, data augmentation techniques such as random cropping, flipping, and resizing were used to create more variations in the training data. Once the training process was complete, the model was evaluated on a validation set to measure its performance. Metrics such as mAP and intersection over union (IoU) were used to evaluate the accuracy and robustness of the model.

H. Model Validation

To validate the model, the "detect.py" script, was used. This script effectively conducted bounding box predictions and class estimations on the designated test images. The core functionality of YOLOv5 was harnessed to accomplish this. Subsequent to the bounding box predictions and class estimations, an essential step known as inference computation was performed. This involved the integration of the predicted bounding box information with corresponding prediction rates.

For a comprehensive model validation process, the "val.py" script was applied. This script, crucially, made use of the optimal model weights contained within the "best.pt" file, ensuring the utilization of the most refined model configuration. This choice of weights maximized model performance. Within the validation process, the script meticulously computed a suite of performance metrics. These metrics encompassed crucial elements such as classes identified, total images assessed, individual instances detected, as well as precision, recall, and mean average precision values. These calculated metrics collectively formed a robust quantitative representation of the model's efficacy and accuracy in object detection and classification [8].

IV. RESULTS

A. Effect of Timeframes

Three different timeframes were used. Each timeframe can be described as follows. During the 5-6 PM timeframe, as depicted in Fig. 3, the environment still retained traces of daylight, albeit with a diminishing intensity. The sun's descent casted elongated shadows, and the street came alive with a mixture of natural and emerging artificial light sources, such as streetlights and the headlights of vehicles.

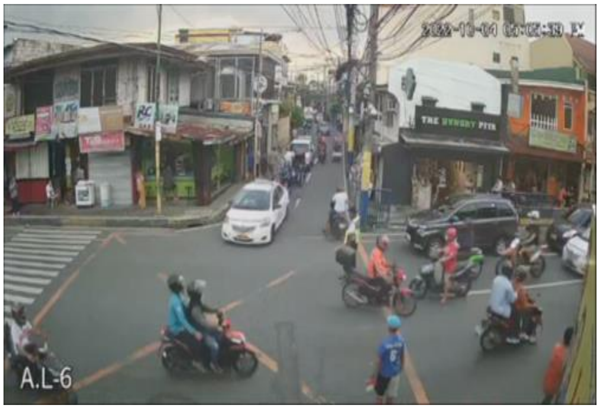

Fig. 3. 5-6 pm footage.

As the clock advanced to 6-7 PM, based on Fig. 4, the setting underwent a noticeable change. The sky took deeper hues of twilight, and the natural light waned further. Streetlights begin to dominate the scene, creating a stark interplay between light and shadow. Details became less discernible, and the environment embraced an ambiance of early evening.

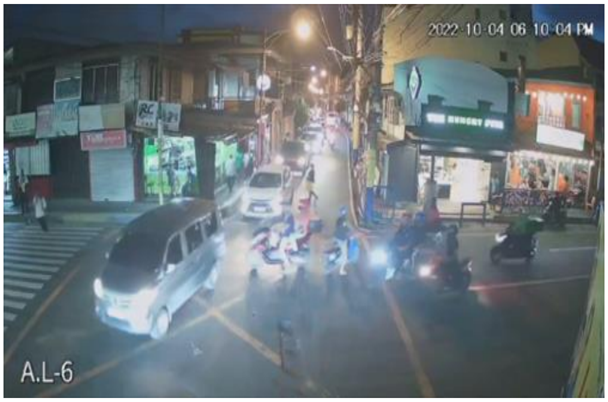

Fig. 4. 6-7 pm footage.

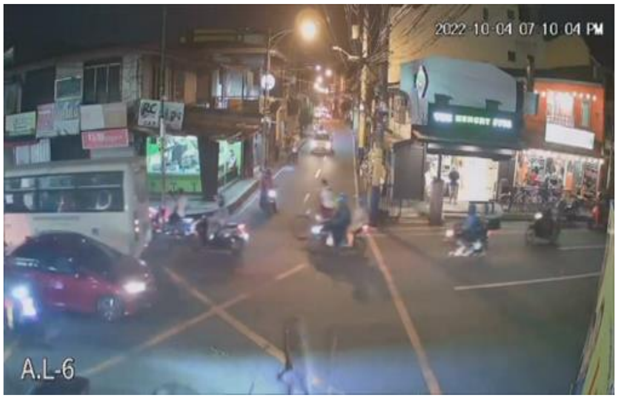

Fig. 5. 7-8 pm footage.

By the time 7-8 PM arrived, as depicted in Fig. 5, darkness had firmly settled in. The streetlights and vehicle headlights became the primary sources of illumination, casting a subdued glow across the surroundings. The scene exuded an atmosphere of low light, with visibility significantly limited compared to earlier hours.

These deliberate timeframes were chosen to comprehensively capture the spectrum of lighting conditions that motorcycle rider's encounter. The resultant dataset's pre-processed videos effectively portrayed the evolving illumination scenarios, enriching the machine-learning model's ability to navigate and respond adeptly across varying levels of lighting intricacies.

B. YOLOv5

The model's performance was evaluated using different hyperparameters in various scenarios and summarized in Table III. In the YOLOv5 Small scale results from 5 to 6 PM, Hyperparameter 3 yielded the best performance, achieving an average precision of 94.4%, an average recall of 89.8%, an average mAP@.5 of 94.3%, and an average mAP@.95 of 73.8%. Moving to the YOLOv5 results from 6 to 7 PM, Hyperparameter 3 also had the best performance, achieving an average precision of 75.6%, an average recall of 65.6%, an average mAP@.5 of 68.3%, and an average mAP@.95 of 40%, especially in the Rider class. In the YOLOv5 Small scale results from 7 to 8 PM, Hyperparameter 2 performed the most achieving an average precision of 62%, an average recall of 59.3%, an average mAP@.5 of 61.4%, and an average mAP@.95 of 49.2%.

Various hyperparameters yielded different results across three varying time frames. While different hyperparameters performed well on certain scenarios. The Hyperparameter 3 performed the most while striking a balance between precision and recall.

C. YOLOv7 with Deep SORT

The results presented in Table III reflects the performance of the YOLOv7 model under different hyperparameters and timeframes. Notably, precision, recall, and mAP (mean Average Precision) scores were evaluated to gauge the model's ability to accurately detect and classify objects within these specified contexts.

During the 5-6 PM timeframe, Hyperparameter 3 exhibited the highest precision (94.4%), recall (89.8%), mAP@.5 (94.3%), and mAP@.95 (73.8%). Shifting to the 6-7 PM timeframe, Hyperparameter 1 stood out with the highest precision (75.6%) and a relatively good recall (65%), leading to a commendable balance between the two metrics. Lastly, in the 7-8 PM timeframe, Hyperparameter 2 demonstrated the highest precision (72.3%), recall (68.2%), mAP (70.6%), and mAP@.95 (63%). These results show that the implementation of Deep SORT to the training of YOLOv7 models had outperformed the results of its predecessor YOLOv5 given the hyperparameter configurations mentioned in Table II

TABLE III. YOLOV5 AND YOLOV7 RESULTS

Model	Parameters			
	Precision (%)	***Recall (%)***	***mAP@.5 (%)***	***mAP@.95 (%)***
Timeframe 5-6 PM				
YOLOv5 (L) H3	94.4	89.8	94.3	73.8
YOLOv7 H3	95.6	91.2	95.1	76.3
Timeframe 6-7 PM				
YOLOv5 (L) H3	75.6	65.6	68.3	40
YOLOv7 H1	86	73	79.5	51
Timeframe 7-8 PM				
YOLOv5 (M) H2	62	59.3	61.4	49.2
YOLOv7 H3	72.3	68.2	70.6	63

V. DISCUSSION

Our study compared three hyperparameter settings in YOLOv5 and YOLOv7 with Deep SORT object identification models which demonstrated the importance of hyperparameter adjustments in achieving superior performance metrics [18]. Particularly for certain classes such as riders and invalid cases, H3 regularly displayed higher precision, recall, and mAP scores. To address issues such as accurate helmet detection, however, fine-tuning and rigorous evaluation are still required. These findings contribute to the continuous developments in object detection models and provide useful insights for computer vision researchers and practitioners.

Based on the outcomes of the different models, it is recommended that researchers and practitioners working with object identification models, particularly YOLOv5 and YOLOv7 with Deep SORT, take into account the ideal hyperparameter settings revealed in study [6] [10] [13] [12]. Specifically, Hyperparameter 3 regularly outperformed other scales and time frames, with higher precision, recall, and mean average precision (mAP) ratings.

Implementing Hyperparameter 3 (higher epochs, quicker learning rates, and smaller batch sizes) can result in enhanced object detection accuracy and better localization of certain classes such as riders and invalid cases. It is crucial to highlight, however, that further study and fine-tuning may be required to overcome difficulties with helmet identification, as this area demonstrated space for development.

Finally, this work emphasizes the need of doing comparative analyses and experimenting with different hyperparameter settings to maximize model performance. As the science of computer vision advances, it becomes increasingly important to adjust and refine hyperparameters to achieve the best results for individual applications.

Overall, this study gives useful insights on hyperparameter tuning in object detection models, as well as practical recommendations for scholars and practitioners in the field. Practitioners can improve the accuracy and performance of their object detection systems by evaluating the findings and using the recommended hyperparameter values, thereby contributing to breakthroughs in computer vision and its diverse applications.

Further research could explore innovative techniques and data augmentation methods tailored to low-light scenarios. Leveraging advancements in low-light image enhancement and night vision technologies could prove beneficial. Additionally, the incorporation of infrared or thermal imaging sensors in object detection models may enhance the accuracy of helmet detection under challenging lighting conditions. Moreover, collaborating with experts in the field of motorcycle safety to collect real-world data from diverse lighting environments and helmet types would be invaluable for training and evaluating detection models. Lastly, an emphasis on fine-tuning hyperparameters, such as those highlighted in this study, should continue to be a crucial aspect of future research efforts to achieve more robust and reliable helmet detection, ultimately contributing to increased safety for riders.

VI. Conclusion

In conclusion, our study comparing YOLOv5 and YOLOv7 with Deep SORT object identification models revealed that YOLOv7 with Hyperparameter 3 consistently outperformed YOLOv5 and other hyperparameter settings in terms of precision, recall, and mean average precision (mAP) scores. Specifically, Hyperparameter 3, characterized by higher epochs, quicker learning rates, and smaller batch sizes, proved to be the superior choice for achieving enhanced object detection accuracy, especially for certain classes like riders and invalid cases. These findings suggest that YOLOv7 with Hyperparameter 3 is the recommended configuration for practitioners and researchers working in the field of object detection, highlighting its potential to contribute significantly to advancements in computer vision applications.

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China's Science and Technology Finance and Economic Corridor Development: A Coupling Relationship Analysis

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***Abstract*—This study aims to explore the coupling relationship between science and technology finance and economic corridor development in my country based on the life cycle theory of industrial clusters. By analyzing the interaction between science and technology finance and the development of economic corridors, our degree of correlation and influence mechanism at different stages are revealed. The main findings of this study include that at different stages of the life cycle of industrial clusters, there are differences in the effect of science and technology finance on the development of economic corridors, showing a gradually strengthening or decreasing trend; there is a strong positive relationship between science and technology finance and the development of economic corridors. Coupling relationship, the development of science and technology finance promotes the construction and development of economic corridors, and vice versa; the coupling relationship between science and technology finance and the development of economic corridors has important policy implications and provides useful information for government departments, business managers and scientific research institutions Reference and guidance. These findings are of great value to the formulation and implementation of science and technology finance policies, the planning and construction of economic corridors, and the cultivation and development of industrial clusters. Government departments can adjust science, technology, finance and economic corridor development policies based on the characteristics of the coupling relationship to promote their coordinated development and virtuous cycle. Based on the research results, business managers and scientific research institutions can optimize resource allocation, enhance innovation capabilities, and achieve sustainable development.**

Keywords*—Technology finance; regional economic development; industrial clusters; life cycle theory

I. INTRODUCTION

Technological finance has received much attention in regional economic development because it integrates modern technology and advocates innovative financial and technological investment. In recent years, Chinese local governments have kept abreast of national policy trends and vigorously promoted the close integration of technology finance and regional economic development around regional innovation strategies. For one thing, local governments actively offer help in studying and improving science and technology, the change of accomplishment in science and technology, and the industrialization of high-tech. It has a diversified service system of science and technology finance with local characteristics. On the other hand, local governments set out to formulate guidelines for developing Internet finance and explore the path for the healthy and sustainable development of the local Internet finance industry. Technological and financial innovation is a crucial correlative factor for China's regional economy's current and future increase. Combining the two can bring about a qualitative leap in regional economic development. However, innovative elements such as technology, information, and talents tend to agglomerate in economically developed regions in recent years. This leads to a significant gap in innovation capability between regions in China. How to effectively and evenly combine technological finance and regional economic development in different regions has become a problem. Hence, it is of practical importance to study the coupling connection between technological finance and regional economic development.

Tracing the historical development track of science and technology finance and regional economy, financial technology can improve financial services through various technological innovations, so the research on financial technology is becoming increasingly new daily. Ra Jeswari R investigated the evolution of tech finance in global markets. He exposed issues like the driving factors of fintech, the disadvantages of conventional financial services, and technological advances [1]. His research can help us improve fintech innovations, but more experimental verification is needed. Golab P researched the role of technology finance and regional economy and proposed that technological innovation is one of the important factors of financial development [2]. His research can point out the development direction for us in a targeted manner, but more detailed verification is needed in the specific operation. Liu Z studied technology finance from the perspective of environmental protection and advocated its benefits for developing a green economy [3]. His research is very helpful for our sustainable development but lacks specific operational means. Arif M studied the status quo of fintech in the development of financial inclusion in China, and he proposed that although China's financial system has made great progress, the gap between developed and under-developed areas is still huge [4]. Boshkov T's research showed that tech finance improves data transmission and analysis. He also provided opportunities for small companies to build low-cost distribution models and risk administration applications [5].

Life cycle theory is widely used in various fields and solves different problems for different scholars. Oskouei Z H started with cash flow and used life cycle theory to predict a company's profitability [6]. His research can provide a reference for company operations, enhancing the growth of the regional economy. Besides that, scholars often mention the life cycle theory of industrial clusters. Yan S studied the development of population urbanization from the view of industrial cluster life cycle theory [7]. His research is conducive to the balanced growth of urban and rural areas, but whether it is effective still needs experimental verification. Starting from the life cycle theory, Cady SH put forward suggestions on the development of products [8]. His research contributed to better product building, advancing the social product economy. From the perspective of life cycle theory, Gao L H empirically analyzed the influence of innovation and development in technology and finance on industrial agglomeration [9]. His research shows that the government should further complete a coordinated growth strategy, promote regional innovation in technology for future consideration, and achieve integration with financial development. It has to be aware of risks in the process. From the perspective of technological finance development, previous research may have paid more attention to the analysis of technological finance development trends, policy support, financial innovation and other aspects. These studies may focus on the role of science and technology finance in promoting technological innovation and industrial development, as well as the innovation and application of science and technology finance products and services. From the perspective of economic corridor construction, past research may have focused on analyzing the impact of economic corridor construction on regional economic development and coordinated regional development. These studies may focus on the impact of economic corridors on regional industrial structure, industrial layout, talent flow, etc. In terms of the life cycle theory of industrial clusters, past research may have focused more on the characteristics and evolutionary rules of the formation, development, maturity and decline stages of industrial clusters. These studies may focus on the analysis of internal relationships within industrial clusters, industrial chains, technological innovation, etc. Current research focuses more on linking the life cycle theory of industrial clusters with technology finance and economic corridor development to establish a relevant theoretical framework. By integrating theories from different fields, we conduct an in-depth exploration of the impact mechanism of science and technology finance on the development of economic corridors at different stages.

This paper is divided into five sections. Section I introduces the background and significance of the research, summarizes the importance of science and technology finance and economic corridor development, and then briefly expounds the basic concept of industrial cluster life cycle theory and its application value in this study. Section II discusses the research methods of the coupling relationship between science and technology finance and regional economic development in China; Section III uses selected methods and data to analyze the coupling relationship between science and technology finance and economic corridor development. Section IV summarizes the results of empirical analysis, answers the research questions, and validates the hypothesis and finally Section VI concludes the paper.

This paper starts from the life cycle theory of industrial clusters and extracts features from different cycles as indicators to study technology finance and regional economy growth. It also analyzes the coupling degree of the two. The innovation of this paper is to integrate physics knowledge into economic research. Based on the CCD model and classification of physics, it determines the level of coupling and coordinated growth of regional economy growth and technology finance, thereby providing an intuitive basis for the comparative analysis of coupling and coordination degrees.

II. Methods of the Coupling Relationship between China's Science and Technology Finance and Regional Economic Development

A. Theory of Life Cycle of Industrial Clusters (LCIC)

The industrial cluster life cycle theory refers to the following. When people find that industrial clusters have their life course, just like creatures in nature, many economists apply life cycle theory to industrial clusters to analyze their development law more accurately [10]. There are various divisions for the life cycle of industrial clusters, most of which are divided into six stages by European SMEs. The United States divides it into five stages, with four and three-stage divisions [11]. This paper adopts China's usual division method and divides LCIC into four phases, as shown in Fig. 1.

According to Fig. 1, the life cycle of an industrial cluster can be grouped into a formation stage, a growth stage, a mature stage, and a decline stage. The characteristics of these four stages are described in detail below:

1) Formation stage: At the beginning of this stage, only a few related enterprises may gather together. These enterprises take advantage of local resources or locations to develop slowly. Since the aggregation in geographic space reduces the transaction cost and risk of cooperation between enterprises, there is a certain aggregation effect. However, the cluster's development momentum is still weak due to the lack of various factors, such as various markets, government policy support, and related support institutions. However, it is also because the starting point of the base of the company's sales revenue at this time is relatively low, so the development speed of the company at this stage is relatively fast.

2) Growth stage: In this stage, many enterprises bring capital, technology, human resources, management mode, etc., into the cluster. The supporting hardware facilities, regional innovation, and network environment have also greatly increased the internal enterprise's economic strength. Universities, research institutions, and industry associations also increase, making the cluster a strong driving force for development [12]. The economic effect produced by the industrial cluster has become the economic growth point of the region, and the government, therefore, gives more support in terms of policies and other aspects. Industrial clusters have entered a stage of rapid growth. Clusters also increase the entry threshold of enterprises due to the improvement of various internal levels.

3) Mature stage: In the mature stage, after the accumulation and precipitation of the formation stage and the growth stage, the scale of the industrial cluster begins to stabilize gradually. The development speed has also gradually slowed, and many funds, technologies, and human resources have gathered within the cluster. Still, the attractiveness of various external resources has begun to decline. It should be noted that the resources the developing enterprises rely on after the formation and growth period are gradually exhausted, and their efficiency begins to decrease. At the same time, the over-aggregation of enterprises in the cluster also led to the decline of the industrial cluster [13].

4) Recession stage: In the recession phase, many companies within the cluster relocate, and the problem of losing technical talents and funds of the remaining enterprises also becomes serious. Malicious competition within enterprises is becoming more and more frequent. If some new major changes, such as major innovations, can occur at this stage, the cluster can be transformed into a new life cycle stage. It would otherwise not change the recessionary trend [14].

B. *Inflection Point of the LCIC*

In the development course of the LCIC, three turning points of acceleration, consolidation, and control usually appear. Fig. 2 shows a schematic diagram of the inflection point in the life cycle of an industrial cluster.

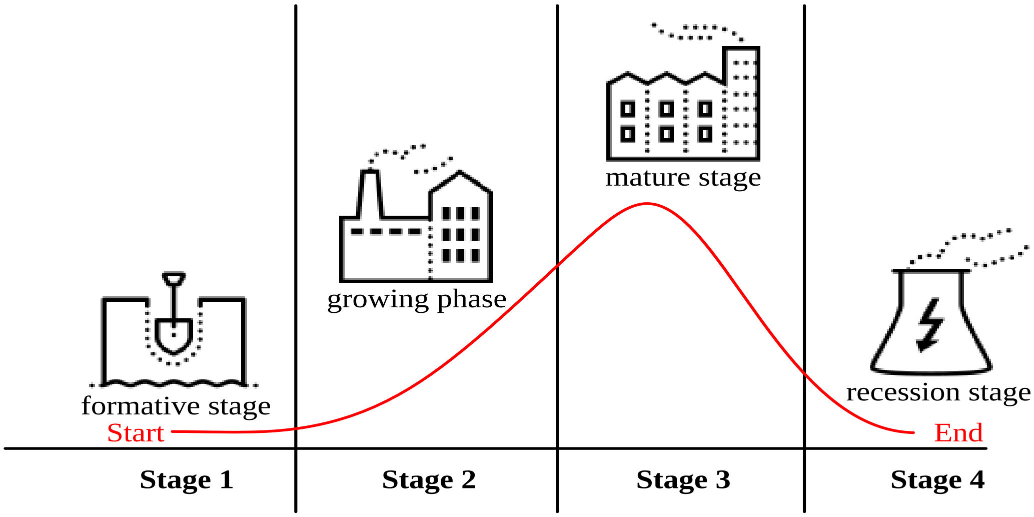


Fig. 1. Four stages of LCIC.

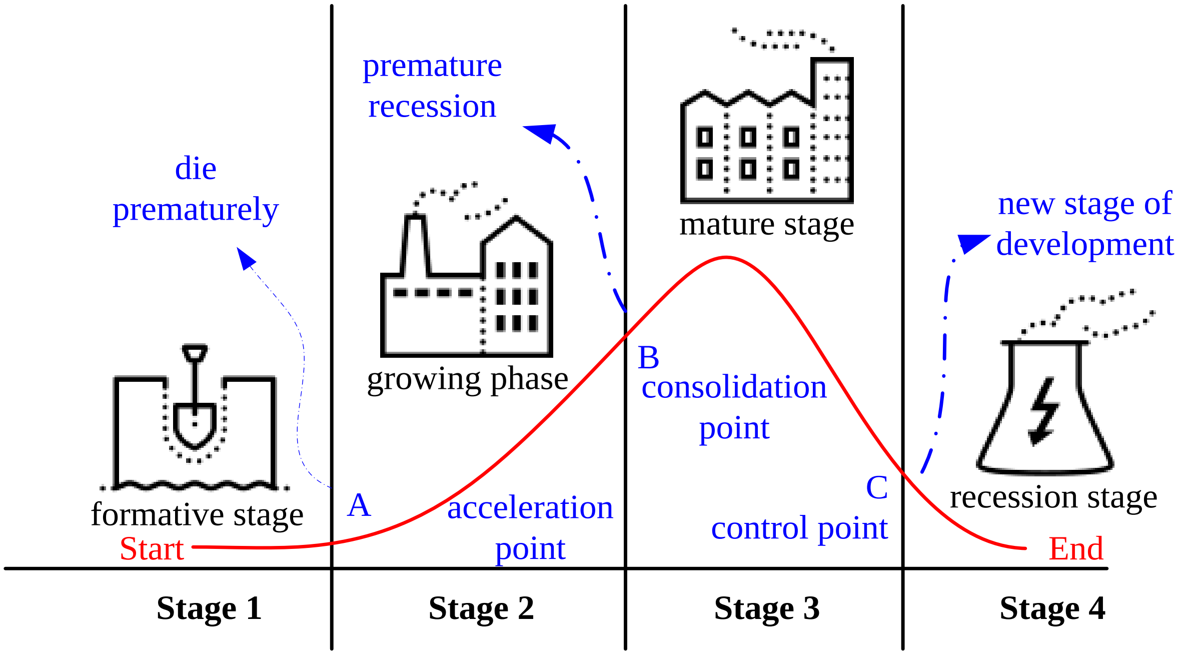


Fig. 2. Inflection points in LCIC.

As shown in Fig. 2, the four stages of LCIC and the three inflection points can be seen in the development process. From the mature phase of the industrial cluster, the mature stage can be classified into two parts: the upper-rush phase and the falling phase. Due to various reasons inside and outside the cluster, the cluster will have a decline stage until after the control point. Finally, the development of the industrial cluster will gradually decline, and it will enter the decline stage until it disappears.

The inflection points of acceleration, consolidation, and control mentioned above are a few special and critical periods in the life cycle development of industrial clusters. After different inflection points, the clusters will face different situations and characteristics. Whether these inflection points can be accurately judged plays an important role in judging the life stage of the industrial cluster and the possible future trend [15]. On the one hand, judging these inflection points can provide us with reasonable suggestions and measures to improve the overall competitiveness of the cluster and prepare for breaking through the inflection points to accumulate strength. On the other hand, according to the internal situation of the cluster after different inflection points, its characteristics can be extracted as an indicator of the coupling system of technology finance and regional economy growth.

C. Coupling and Coordinating Index System of Technological Finance and Regional Economy Growth

1) Index selection: According to the system coupling theory, this paper regards technology finance and regional economic development as two subsystems of system coupling $S = \{T, F\}$. Among them, T is technology finance, and F is regional economy. By dividing different inflection points in the life cycle of industrial clusters in the previous section, based on grasping the stage characteristics and influencing factors of technological finance and regional economic development, it comprehensively considers China's actual national conditions. It selects static and dynamic indicators and then scientifically and reasonably constructs an indicator system for the coupling and coordination degree of science and technology finance and regional economy suitable for panel data spanning two dimensions of time and space. Table I shows the contents of each indicator.

Science and technology finance support policies refer to the policies and measures introduced by the government in the region to support the development of science and technology finance, including tax incentives, loan support, entrepreneurial subsidies, etc.; regional economy measures the driving effect of the construction of economic corridors in the region on the surrounding regional economy, including employment growth, industrial upgrading etc.

2) Entropy weight determination: Determining the weight is a necessary link in the comprehensive evaluation process and a key step in quantifying the comprehensive evaluation index. The results of determining the weights can have an important impact on rationality and scientific evaluation. The entropy weighting method belongs to the objective weighting method. It generally uses mathematical operation technology to determine the weight, which can avoid the interference of human and subjective factors. It has been widely discussed and applied by academia in recent years [16].

First, it makes assumptions about the selected indicator variables. It represents the number of years, K means the number of indicators, and J means the number of regions. Then x_{ijk} stands for the k-th index variable in the j region of the ith year, and the value of the index variable is X. The specific calculation process is as follows:

a) Standardization of indicators: Since each evaluation index has different dimensions and units, it is necessary to continue to standardize the index variables, and the normalization method is used in this paper. The calculation process is shown in Formula (1):

$$x'_{ijk} = x_{ijk} - xminmax_{min} \tag{1}$$

b) Calculate the index entropy value: After the standardization process, each index variable's weight 'y ijk is calculated, and the calculation process is shown in Formula (2). According to the weight results of the index variables, the entropy value e_k of the k-th index can be calculated, and the calculation process is shown in Formula (3), $k \geq 0$, $k = ln(IJ)$.

$$y'_{ijk} = x_{ijk} / \sum_i \sum_j x'_{ijk} \tag{2}$$

$$e_k = -k \sum_e \sum_j y'_{ijk} \, ln\left(y_{ijk}\right) \tag{3}$$

TABLE I. THE INDEX SYSTEM OF THE CCD OF SCIENCE AND TECHNOLOGY FINANCE AND REGIONAL ECONOMY

System Layer	Target Layer	Indicator layer	Variable explanation
Technology Finance (T)	Technology innovation investment	Human input	Full-time equivalent of R&D personnel (person-year)
		financial input	Fiscal spending on technology (%)
	Technological innovation output	Licensing	Number of Patents Accepted (%)
		technology export	Total merchandise exports (%)
Regional Economy (F)	economy of scale	Financial depth	Deposit and loan balance (%)
		financial competitiveness	Number of listed companies (s)
	economic performance	capital allocation ratio	Loan balance (%)
		Insurance depth	Premium income (%)

TABLE II. THE WEIGHT OF THE INDEX WEIGHT OF THE COUPLING AND COORDINATION DEGREE OF SCIENCE AND TECHNOLOGY FINANCE AND REGIONAL ECONOMY

Indicator variable	2016	2017	2018	2019	2020	2021
Human input	0.0658	0.062	0.0562	0.0636	0.0694	0.0714
financial input	0.0637	0.0674	0.0565	0.0755	0.0725	0.0969
Licensing	0.0832	0.0696	0.0583	0.0597	0.0674	0.0658
technology export	0.0267	0.0361	0.0303	0.0384	0.0636	0.0320
Financial depth	0.1335	0.1340	0.1496	0.1622	0.0864	O.1641
financial competitiveness	0.0739	0.0686	0.066 1	0.0722	0.0699	0.0638
capital allocation ratio	0.0771	0.0774	0.0708	0.0715	0.0696	0.0683
Insurance depth	0.0580	0.0582	0.0504	0.0597	0.0689	0.0496

c) Calculate the indicator weight: Then, through the entropy value of each index, the information entropy redundancy d_k of each index is calculated, and the calculation process is shown in the following formula:

$$d_k = 1 - e_k \tag{4}$$

$$\lambda_k = d_k / \sum_k d_k \tag{5}$$

Next, this article selects the panel data of six regions in China from 2016 to 2021. The professional programming software MATLAB2016 uses the entropy weighting approach to calculate the weight results of each index in the technological finance and regional economic index system. The clear results are in Table II.

3) Efficacy function: Based on the entropy weighting method, this paper continues to introduce the efficacy function. The power coefficient method can reduce the bias of a single approach, which is more suitable for analyzing complex systems. The power function can measure the function of the subsystem to the composite system from disordered to ordered evolution [17]. The degree of coupling coordination is just a measure of the degree of effect in the evolution of the system coupling from disorder to order. The specific calculation process of the power function model is as follows:

a) Efficacy coefficient: Assuming a variable, $u_{nm}(n = 1,2,3\ldots,p; m = 1,2,3\ldots q)$ is the contribution of the mth index in the nth subsystem to the coupling order degree of the system, that is, the efficiency coefficient of the subsystem. Among them, $u_{nm} \in [0,1]$, when the efficiency coefficient is closer to 1, indicates that the contribution of the subsystem to the system coupling is greater. Technological finance and regional economy, as two subsystems coupled by the system, can calculate the efficacy coefficient u_{nm} of technological finance and regional economy on the degree of order through the Formula (6) of the efficacy coefficient, that is, when $n = 1,2, m = 1,2,3\ldots 7$.

$$u_{nm} = \begin{cases} \frac{Z_{nm} - b_{nm}}{a_{nm} - b_{nm}}, & proves \text{ u}_{\text{nm}} \text{ positive} \\ \frac{a_{nm} - Z_{nm}}{a_{nm} - b_{nm}}, & \text{proves u}_{\text{nm}} \text{ negative} \end{cases} \tag{6}$$

In Formula (6), Z_{nm} stands for the value of the mth index of the nth subsystem, and a_{nm} and b_{nm} represent the upper and lower limits of each index variable in the subsystem, respectively.

b) Efficacy value: Through the efficacy coefficients of regional innovation in science and technology and regional financial innovation, and using the Formula (7) of the efficacy value, the efficacy values u_n of regional innovation in science and technology and regional financial innovation on the degree of order can be calculated, namely u_1 and u_2.

$$u_n = \sum_{m=1}^{q} \lambda_{nm} u_{nm}, \sum_{m=1}^{q} \lambda_{nm} = 1 \tag{7}$$

In Formula (7), λ_{nm} is the index weight calculated by the entropy weighting method in the previous section.

4) CCD function: The CCD model is an optimization and upgrade for the defects of the coupling degree model. This paper draws on scholars' research on the CCD of multiple systems, and firstly constructs the coupling degree model of regional innovation in science and technology and financial innovation. On this basis, it continues to develop the coupling coordination model of the two [18].

a) Coupling degree model: To measure the coupling degree of regional technological innovation and financial innovation, this paper adopts the interdisciplinary expansion model of the physical capacity system model. The specific model is shown in Formula (8). When p=2, it is the coupling degree model of regional technology and finance innovations, as shown in the following formulas.

$$C_p = \sqrt{\frac{(u_1 \cdot u_2 \cdot \ldots \cdot u_p)}{\prod(u_1 + u_2 + \ldots + u_p)}} \tag{8}$$

$$C_2 = \sqrt{\frac{(u_1 \cdot u_2)}{\prod_{n=1,2,m=1,2\ldots 7} u_1 + u_2}} \tag{9}$$

In Formula (8) and Formula (9), p is the number of subsystems constituting the composite system. C is CCD between subsystems. The value range of CCD is $C \in [0，1]$. The larger the CCD value is, the stronger the CCD is. Among them, when $C = 0$, the CCD value is small, indicating no coupling between subsystems, and the composite structure tends to have a disordered structure. When $C = 1$, the value of CCD is large, indicating that the degree of coupling between subsystems is strong, and the composite system tends to be newly ordered.

b) Coupling coordination degree model

$$\begin{cases} T = \mathrm{au}_1 + \beta u_2 + \ldots + \pi \mu_p \\ D = \sqrt{C \cdot T} \end{cases} \tag{10}$$

Since the research objects of this paper are scientific and technological finance and regional economy, respectively, the CCD model of regional innovation of science and technology and financial innovation is deduced. The model is as follows:

$$\begin{cases} T = \mathrm{au}_1 + \beta u_2 \\ D = \sqrt{C \cdot T} \end{cases} \tag{11}$$

In the above formula, $D \in [0,1]$, the larger the value of coupling coordination degree, the stronger the CCD and coordination between regional technological innovation and financial innovation. Among them, when $D = 0$, it shows that there is no coupling relationship between the two systems, and there is no coordination; when $D = 1$, it means that the CCD in the two systems reaches a large value, and the coupling state presents a high level. Both systems develop in an orderly fashion [19]. Based on the actual situation of the research object in this article, only CCD $D \in (0，1]$ is considered here.

III. Coupling Experimental Design and Data Sources

This article uses the panel data of six regions in China (Northeast China, North China, Central South, East China, Southwest China, and Northwest China) from 2016 to 2021 as a sample. All data used in the study came from relevant statistical yearbooks for each year from 2016 to 2021. The indicator data comes from fiscal science and technology expenditures, public financial expenditures, technology market turnover, and total commodity exports in the "China Industrial Statistical Yearbook" of each year. In addition, due to changes in China's statistical caliber, the indicator data of "high-tech industry output value" from 2016 to 2021 is replaced by the main business income of high-tech industries. Statistics such as "technological market turnover" and "total commodity exports" in Tibet are missing. It was removed from this paper's research so as not to affect the overall results.

To realize the idea of the thesis, it is necessary to combine the relevant theoretical knowledge of industrial cluster life cycle theory, technology finance and economic corridor development, and use technical information for data collection, analysis and demonstration. The following is technical information that may be used:

1) Data collection technology: Web crawler technology: used to obtain a large amount of relevant literature, statistical data, policy documents and other information from the Internet to support the theoretical basis of research.

a) Database technology: used to establish and manage databases related to technology, finance, economic corridor development and other related data for data analysis and mining.

b) Questionnaire technology: used to survey relevant enterprises, government departments, experts and scholars, etc., to obtain their views and opinions on the coupling relationship between technology finance and economic corridor development.

2) Data analysis technology: Statistical analysis software: such as SPSS, R, etc., used to conduct descriptive statistics, correlation analysis, regression analysis, etc. on the collected data to discover the relationship between the data.

a) Data mining technology: such as cluster analysis, association rule mining, etc., used to mine hidden patterns and trends in data and reveal the potential correlation between technology finance and the development of economic corridors.

3) Model building technology: Industrial cluster life cycle model: Based on the industrial cluster life cycle theory, a life cycle model of technology finance and economic corridor development is established to describe and analyze the characteristics and development patterns of different stages.

a) Economic corridor input-output model: Based on the economic corridor theory, an input-output model is established to quantitatively evaluate the driving effect of economic corridor construction on the regional economy.

4) Visualization technology: Data visualization tools: such as Tableau, Power BI, etc., used to visually display research results in the form of charts, maps, etc., to improve the understandability and attractiveness of research results.

IV. Experimental Result

A. Calculation Results of Coupling Coordination Degree

Using MATLAB2016 software and the efficacy function formula in the second section, this paper can calculate the efficacy values of 6 science and technology finance and regional economies in China from 2016 to 2022. The coupling degree model formula in Section II can calculate the CCD of technology finance and regional economy. It can calculate the CCD index through the CCD formula. In terms of the CCD and CCD index, the coupling and coordination degree between technology finance and regional economy can be finally calculated, as shown in Table III.

B. Variation Trend of CCD

Based on the above empirical results, this article analyzes the growing tendency of CCD of scientific and technological finance and regional economy in the time dimension through the change of the mean value, ranking, and numerical value of CCD. In addition, through the consequences of efficacy value, this article compares and analyzes the development status between technology finance and the regional economy [20].

The mean is one of the important indicators reflecting the central tendency of the data, which can be used to describe the trend characteristics of the data. The mean analysis of different years can reflect the growing trend of the CCD of science and technology finance and regional economy over time. Fig. 3 shows the average change in CCD in technology finance and regional economy.

TABLE III. EMPIRICAL RESULTS OF THE CCD IN SCIENCE AND TECHNOLOGY FINANCE AND REGIONAL ECONOMY

Regions	2016	2017	2018	2019	2020	2021	2022
Northeast	0.4471	0.4408	0.4542	0.4511	0.4511	0.4440	0.4540
North China	0.2553	0.2478	0.2552	0.2751	0.2751	0.2594	0.2364
Central South	0.1531	0.1535	0.1840	0.1584	0.1584	0.1688	0.1620
East China	0.1732	0.1774	0.1907	0.1971	0.1971	0.1913	0.1133
Southwest	0.1245	0.1389	0.1465	0.1353	0.1353	0.1230	0.1530
Northwest	0.2552	0.2271	0.2169	0.2203	0.2203	0.2058	0.1098

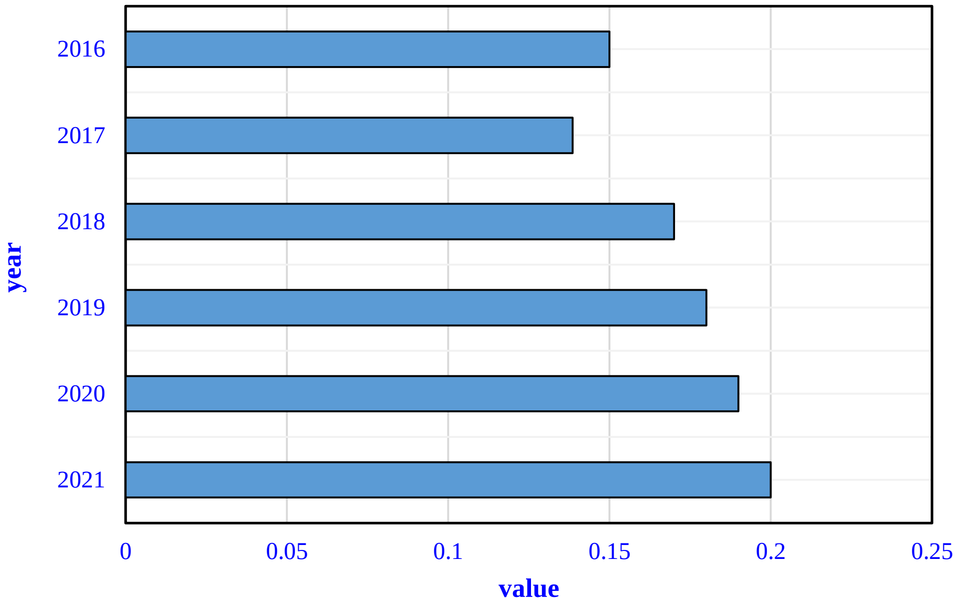


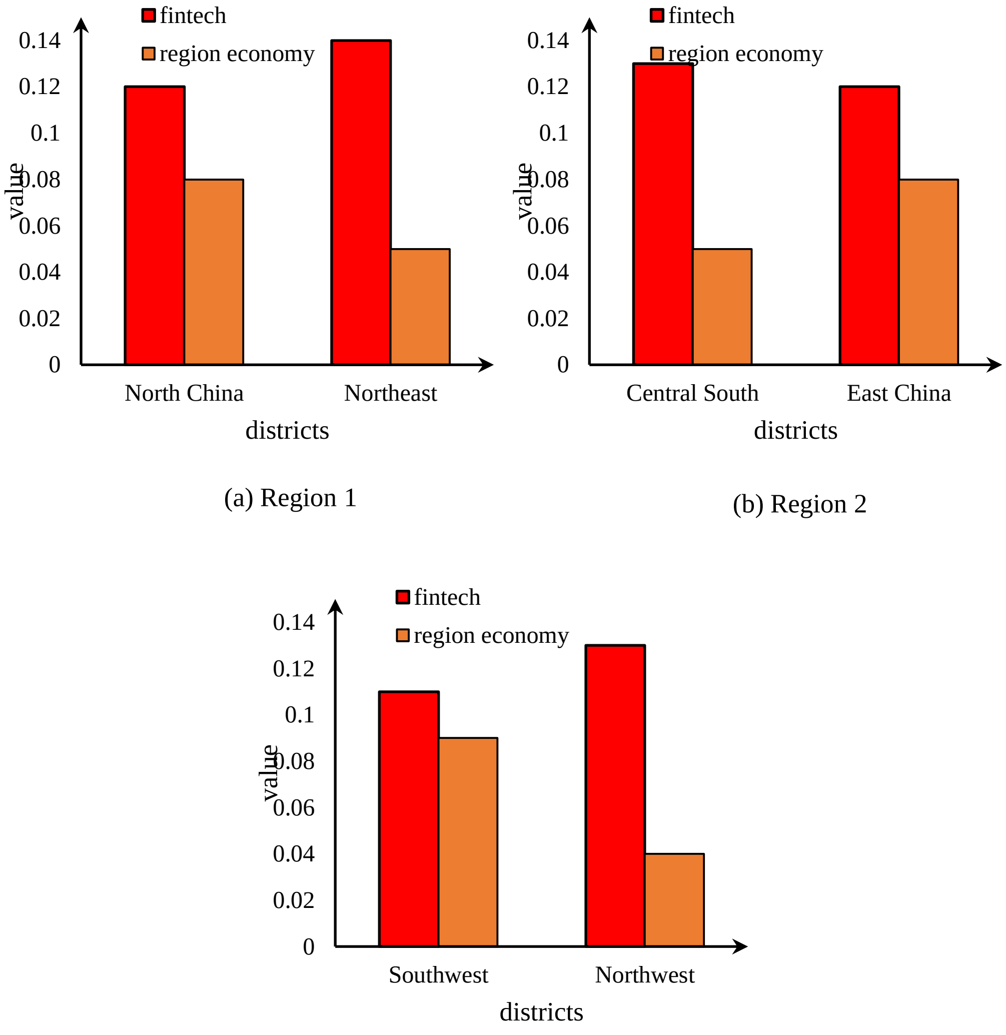
Fig. 3. The mean change of CCD between science and technology finance and regional economy.

According to Fig. 3, from 2016 to 2022, the average value of CCD in technological and financial innovation in China reached 0.1508. Among them, in 2017, the mean value of CCD is the smallest, and its value is 0.1386. In 2018 and 2019, the mean value of CCD was the largest, and its value was 0.1760, which was 0.0374 different from the small value. From 2016 to 2018, the mean value of CCD increased. After 2018, the average value of CCD is generally higher than other years in the past. Apart from a mild drop in individual years, the average value of CCD in scientific and technological finance and the regional economy maintains a slow increase trend.

C. Comparison of Efficacy Values

The efficacy value can reflect the development level of regional technological innovation and financial innovation. Fig. 4 compares the efficacy values of technology finance and the regional economy in each region from 2016 to 2022.

As shown in Fig. 4, the efficacy values of technology finance in the six regions have been higher than the regional economies in the past five years, and technology finance has always been in a leading position. In 2017, the efficacy value of science and technology finance was the largest, with a value of 0.1286, and the efficacy value of the regional economy was the smallest, with a value of 0.0809. The gap between the two was large, as high as 0.0477. The regional economic development momentum slowed down. The gap between the two slowly narrowed until the gap between the two was small, only 0.0172 in 2022. Regional science, technology, and finance innovation are developing in a more coordinated direction.



(a) Region 1

(b) Region 2

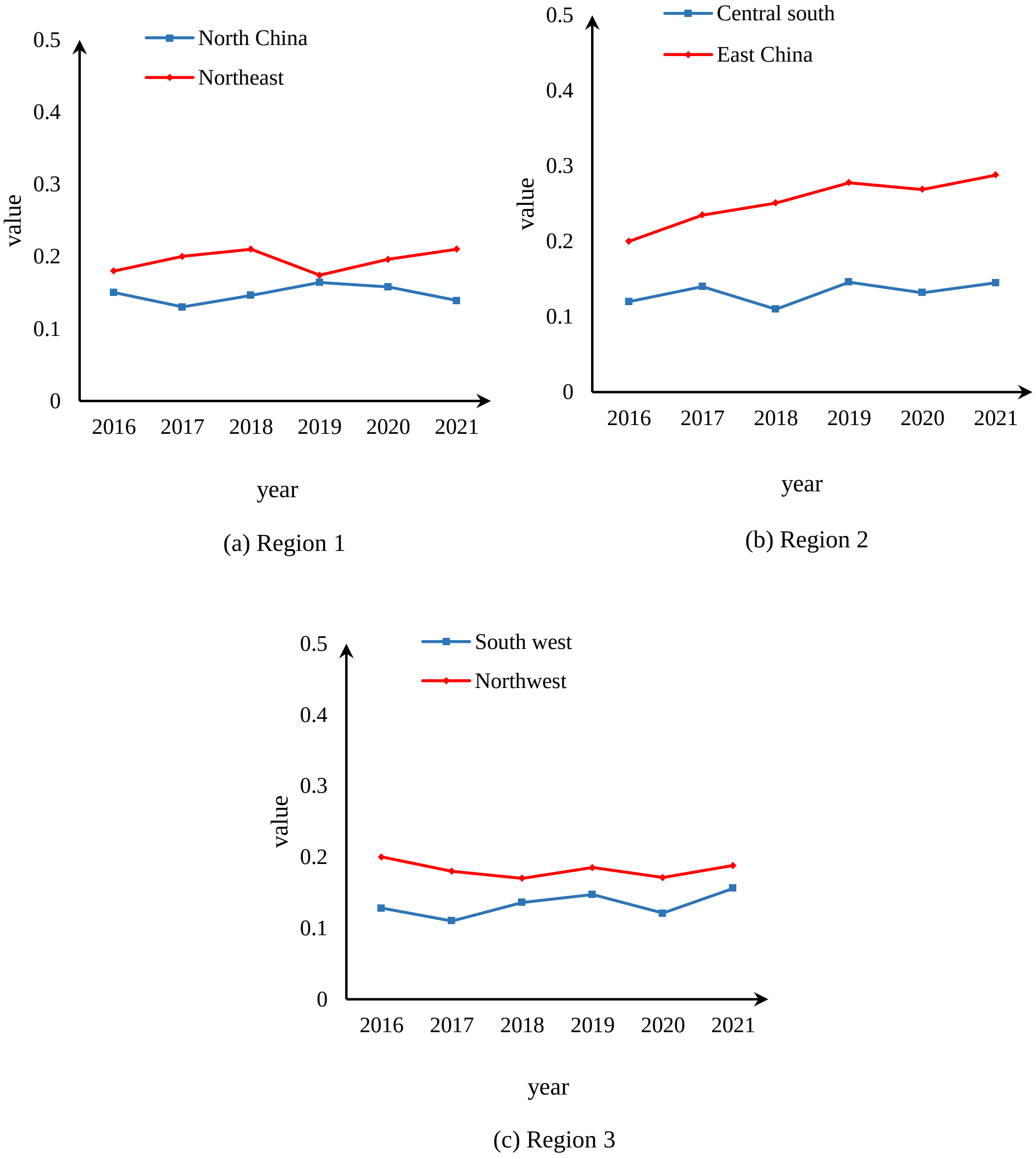
(c) Region 3

Fig. 4. Comparison of efficacy values between technology finance and regional economy.

D. Variation Results of CCD in Different Regions

Based on the size of CCD, the changes in CCD in each of the six regions from 2016 to 2022 are counted, and the results in Fig. 5 are obtained:

From the numerical change of CCD in Fig. 5, from 2016 to 2022, the value of CCD of innovation in science and technology and financial innovation in East China reaches an average of 0.2676. Except for occasional large fluctuations, the overall fluctuation of CCD in East China is not large, and the changing trend is relatively moderate. From 2016 to 2022, the value of CCD of innovation in science and technology and financial innovation in the central and southern regions reached an average of 0.1649. Compared with the eastern provinces, the variation range of the numerical fluctuation of CCD in the central and southern regions is obvious. The value of CCD of innovation in science and technology and financial innovation in the northwest region reaches an average of 0.1687. The numerical change of CCD in the northwest region fluctuates very obviously, and the changing trend generally shows a tortuous trend. Generally, CCD in East China is the most stable, maintaining a leading position in the country. The ranking of CCD in the central and southern regions fluctuates greatly and is the most backward overall. CCD in the western region also fluctuates greatly and is backward.



(a) Region 1

(b) Region 2

(c) Region 3

Fig. 5. Numerical changes in CCD in science and technology finance and regional economy in various regions.

V. Conclusion

Based on LCIC, this paper extracts features through different life cycle stages as indicators for studying the coupling connection between technology finance and regional economy. In the end, the coupling relationship between them is studied. Judging from the existing research on science and technology finance and regional economy, scholars have confirmed a dynamic relationship between the two: mutual demand, mutual promotion, and integrated development. Technological finance and regional economy are coupled through the connection between internal elements, and the degree of coupling between the two determines the properties of spillover effects. The positive spillover effect of coupling technology finance and regional economy can be 1+1>2. This paper regards China as a study of the whole region, which is more in line with the basic national conditions of China's uneven regional development and the current regional development pattern. In this paper, when investigating the course of the coupling and coordinated development of regional technological innovation and financial innovation, due to limited scientific research ability and theoretical foundation, the research on the characteristics and factors of the coupling and coordinated development stage is relatively simple. Individual views are yet to be discussed and discussed. In the future, it looks forward to further research and more profound views. In terms of in-depth study of the coupling relationship mechanism, further explore the coupling relationship mechanism between science and technology finance and the development of economic corridors, including the impact of different types of science and technology finance products on the development of economic corridors, the synergy between government policies and the development of industrial clusters, etc.; In addition, it is necessary to Strengthen interdisciplinary research cooperation with economics, management, finance and other related fields, and fully tap the application potential of industrial cluster life cycle theory in the development of science and technology finance and economic corridors. It is difficult to obtain data on science, technology, finance and economic corridor development, and problems such as insufficient data collection and uneven quality need to be overcome. At present, there are still limitations in research methods, and it is necessary to combine more quantitative and qualitative research methods to improve the scientific nature and accuracy of the research. The theoretical integration between science and technology finance, economic corridors and industrial cluster life cycle theory is not yet complete, and the construction and integration of theoretical frameworks need to be strengthened.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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AUTHORSHIP CONTRIBUTION STATEMENT

Rui Tian: Writing-Original draft preparation, Conceptualization, Supervision.

Birong Xu: Software, language review.

AVAILABILITY OF DATA AND MATERIALS

On Request

DECLARATIONS

Not applicable.

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Correlation Analysis Between Student Psychological State and Grades Based on Data Mining Algorithms

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Abstract*—As society has evolved and educational reform has become more profound, the psychological state and academic performance of vocational college students have become the focus of attention for educators. This study aims to construct a correlation model between the positive psychological state and academic performance of vocational college students based on data mining algorithms to offer a conceptual foundation and practical guidance for the optimization of vocational education. The relationship between positive psychological state and academic performance was analyzed through a literature review, as well as the application of data mining algorithms in the field of education. A certain amount of data on vocational college students was collected using questionnaire surveys and empirical research methods, including their basic information, positive psychological status indicators, and academic performance data. Subsequently, data mining algorithms were used to preprocess and analyze the collected data, and a correlation model between the positive psychological state and academic performance of vocational college students was constructed. Finally, through validation and evaluation of the model, it was found that there is a significant positive correlation between positive psychological state and academic performance, and the model has high predictive accuracy. The study's results suggest that the positive psychological state of vocational college students has a significant impact on their academic performance. Educators should consider students' mental health and take effective measures to enhance their positive psychological state, thereby improving their academic performance. This study provides a new research perspective and method for the field of vocational education, which helps to promote the development and reform of vocational education.

Keywords*—Data mining algorithms; vocational students; positive psychological state; academic performance; correlation model

I. Introduction

In the context of modern education, the relationship between students' psychological state and academic performance is increasingly receiving attention. The psychological state of students, such as emotions, motivation, anxiety, and stress, can have a profound impact on their academic performance. Therefore, understanding and exploring the correlation between these two is of great significance for improving educational quality, optimizing student mental health support, and implementing personalized educational strategies [1]. With the rapid development of information technology, the application of data mining algorithms in the field of education is gradually becoming prominent. These algorithms can extract valuable information from large-scale and complex educational data, thereby providing decision support for educators. The correlation model between student psychological state and academic performance based on data mining utilizes these advanced algorithms to analyze the relationship between student psychological state and academic performance from multiple dimensions and perspectives, in order to provide scientific basis for educational practice [2].

In the context of the information society, vocational education, as an important way to cultivate applied talents, has received widespread attention in terms of its educational quality and training effectiveness [3]. The positive psychological state and academic performance of students are important indicators for measuring the quality of vocational education, and the application of data mining technology in the field of education provides new perspectives and methods for studying this issue. This study aims to provide theoretical support and practical guidance for the reform and development of vocational education by constructing a correlation model between the positive psychological state and academic performance of vocational students based on data mining algorithms [4]. Firstly, the development process of research on the positive psychological state and academic performance of vocational college students at home and abroad was reviewed, and research achievements and theoretical systems in related fields were summarized. On this basis, the challenges and problems faced by current vocational education, such as students' mental health issues, unreasonable allocation of educational resources, and imperfect teaching methods and evaluation systems, were analyzed. To address these issues, a research approach and method for constructing a correlation model between the positive psychological state and academic performance of vocational college students based on data mining algorithms has been proposed [5]. A detailed introduction was given to the application of data mining technology in the field of education, including the basic concepts, technical principles, and methods of data mining, as well as the current application status and development trends in education. Especially for the core technology of constructing a correlation model between the positive psychological state and academic performance of vocational college students, - data mining algorithms - in-depth exploration was conducted, and the advantages, disadvantages, and application scenarios of various algorithms were analyzed.

On this basis, this study proposes a method for constructing a correlation model between positive psychological state and academic performance of vocational college students based on data mining algorithms. By collecting and organizing data on the psychological state and academic performance of vocational college students, a dataset containing multidimensional features was constructed. Then, appropriate data mining algorithms were used to analyze and mine the dataset, discovering the correlation between students' positive psychological state and academic performance. A correlation model between the positive psychological state and academic performance of vocational college students was constructed based on the mining results, and the effectiveness and reliability of the model were verified. By constructing a correlation model between the positive psychological state and academic performance of vocational college students based on data mining algorithms, this study provides useful theoretical support and practical guidance for the reform and development of vocational education. At the same time, this study also pointed out the shortcomings of current research and the issues that need further exploration, providing direction and ideas for subsequent research.

This article constructs a correlation model between student psychological state and academic performance based on data mining algorithms. The innovation contribution lies in:

1) By mining historical student performance data, discover the relationship between student academic performance and various factors, and provide targeted teaching suggestions for teachers. By mining teaching data, the effectiveness of teaching methods and strategies can be evaluated, providing a basis for teaching reform.

2) This article implements a closed-loop early warning system targeting college students. This structure effectively avoids the drawbacks of traditional systems centered around counselors or related institutions.

3) The student psychological state module uses the powerful non-linear approximation ability of artificial intelligence algorithms to fit the relationship between the two, achieving the conversion of psychological category data to student psychological state.

Section I of the study elaborates on vocational education as an important way to cultivate applied talents in the context of the information society. This article introduces the techniques for constructing a model related to the positive psychological state and academic performance of vocational college students. Section II provides an immediate overview of the proposed data algorithms and discusses the main application areas of data mining algorithms. By analyzing student behavior data on online learning platforms, we can discover their learning paths, understand their learning progress and difficulties, and provide personalized learning advice and assistance to students. Section III analyzed the correlation between the positive psychological state and academic performance of vocational college students. Section IV is about the uses of various dimensions of psychological capital as independent variables and SCL-90 total score as dependent variable. The analysis elaborates on the results of multiple regression analysis of variables. Section V conducted model construction based on data mining algorithms. According to the implementation process of the system, the design scheme was experimentally validated in vocational colleges. Section VI and Section VII summarizes the entire text by providing discussion and conclusion. This study provides a new research perspective and method for the field of vocational education, which helps to promote the development and reform of vocational education.

II. Related Work

In vocational education, there is a complex and subtle correlation between students' psychological state, academic performance, relative deprivation, and academic procrastination behavior. This association not only affects the academic performance of students, but also directly relates to their mental health and future career development. Therefore, Xu et al. conducted an in-depth conditional process analysis on this issue. Firstly, it clarifies the concept of "relative deprivation". Relative deprivation is a psychological state in which an individual feels inferior or insufficient in certain aspects after comparing themselves with others. In the context of vocational college students, this sense of deprivation can be attributed to various factors such as unsatisfactory academic performance, social pressure, and uncertainty in future career planning. When students feel this deprivation, their psychological state is often negatively affected, such as anxiety, depression, and inferiority [6]. In vocational education, the relationship between students' psychological state and academic performance is not only related to their academic achievement, but also closely related to the cultivation of their key abilities. Key abilities usually refer to the core skills and psychological qualities that students need when facing future career challenges. With the development of educational technology, data mining algorithms have provided powerful tools for exploring this relationship in depth [7]. With the development of preschool education in vocational colleges, the correlation between students' psychological state and academic performance is increasingly attracting the attention of educators. The stability and well-being of psychological state are particularly important for students majoring in preschool education, as it not only affects their individual learning outcomes, but also directly relates to their future professional qualities and abilities as educators. Therefore, Wu and Yan used data mining algorithms to deeply explore the correlation between the psychological state of vocational preschool education students and their academic performance, in order to provide scientific basis for educational practice [8]. Students majoring in preschool education in vocational colleges will bear an important responsibility in cultivating the next generation in the future, and their psychological state will directly affect their educational behavior and quality [9]. Meanwhile, academic performance, as an important indicator of student learning effectiveness, is also closely related to their psychological state. Therefore, studying the correlation between psychological state and academic performance is of great significance for improving the teaching quality of preschool education in vocational colleges, optimizing student mental health education, and cultivating students to become educators with good psychological literacy [10].

In the current field of education, the relationship between students' psychological state and their academic performance has become an important issue of concern for researchers and practitioners. Previous research literature has provided us with rich knowledge background and research foundation, revealing the multiple effects of psychological state on academic performance, including motivation, emotional regulation, cognitive processing, and other aspects [11]. These studies not only emphasize the importance of psychological state in the learning process of students, but also point out the limitations and shortcomings of traditional assessment methods [12]. Although some research has achieved certain results, there are still some problems and challenges. For example, previous studies have mostly used traditional data collection methods such as questionnaire surveys and interviews, which are difficult to comprehensively and objectively reflect the psychological state of students. In addition, research methods are mostly descriptive statistics or simple correlation analysis, which makes it difficult to deeply reveal the complex relationship between psychological state and academic performance. Therefore, it is necessary to introduce advanced technologies such as data mining algorithms to analyze the correlation between the two in a more scientific and accurate way [13]. With the rapid development of information technology, the field of education is undergoing unprecedented changes. Education data mining, as an important technology, provides strong support for the analysis and prediction of student academic performance. Feng et al. aim to explore how to use educational data mining methods to effectively analyze and predict student academic performance, thereby providing valuable references for educational decision-making and practice [14]. The analysis and prediction of student academic performance based on educational data mining has broad application prospects in educational practice [15]. Firstly, it can provide scientific teaching decision-making support for teachers, helping them better understand students' learning situations and needs, and develop personalized teaching plans. Secondly, it can provide personalized learning advice and guidance to students, helping them identify their learning problems and improve their learning methods. In addition, it can also provide data support for education management departments to help them formulate more reasonable and effective education policies [16].

This study aims to construct a correlation model between student psychological state and academic performance based on large-scale educational data using data mining algorithms. We hope that through this model, we can further reveal the internal relationship between mental state and academic performance, and provide more accurate and personalized guidance for educational practice. Meanwhile, this study is also an important supplement and expansion to existing research, providing new ideas and methods for the future development of the education field.

In summary, the analysis of the correlation model between student psychological state and academic performance based on data mining algorithms has important theoretical and practical significance. Through this study, we hope to provide educators with more scientific and effective decision support, promote the comprehensive and healthy development of students, and also expand new ideas and methods for the application of data mining algorithms in the field of education.

III. Overview of Data Mining Algorithms

With the increasing development of data mining technology, various data mining tools have sprung up like mushrooms after rain. How to choose the most suitable data mining tool for needs has become a question worth pondering. Generally speaking, data mining tools are mainly divided into two categories: one is domain-specific data mining tools and the other is general data mining tools. Domain-specific data mining tools are customized and developed for specific domains or requirements. When designing algorithms for such tools, the specificity of data and requirements can be fully considered for optimization. These tools typically use special algorithms to process specific data to achieve specific goals. Due to its high degree of customization, the reliability of the discovered knowledge is usually high. However, universal data mining tools do not target specific data meanings but instead use universal mining algorithms to handle common data types. The advantage of such a tool lies in its wide applicability. For example, the Mine Set system developed by SGI, the QUEST system developed by IBM Almaden Research Center, and the DB Miner system developed by Simon Fraser University in Canada are typical representatives of universal data mining tools.

A. Main Application Fields of Data Mining Algorithms

The application of data mining algorithms in vocational education has achieved significant results. As big data technology develops, the collection and analysis of educational data have become increasingly important, and the application of data mining algorithms in vocational education is also becoming increasingly widespread. This article will elaborate on the main application fields of data mining algorithms in vocational education.

Student academic performance prediction: By mining historical student performance data, the relationship between student academic performance and various factors can be discovered, providing targeted teaching suggestions for teachers. Data mining algorithms can help teachers predict students' academic performance, identify their learning difficulties in advance, develop personalized teaching plans, and improve teaching quality.

Student turnover warning: The issue of student turnover in vocational education has always been a focus of attention for education managers. By analyzing students' behavioral data through data mining algorithms, it is possible to predict whether there is a risk of student turnover and take corresponding intervention measures to reduce the rate of student turnover. For example, by mining data on students' online behavior, course participation, and grades, it is possible to identify risk factors such as psychological problems and learning difficulties that students may have and provide targeted intervention suggestions for education managers.

Course recommendation: Data mining algorithms can recommend suitable courses for students based on their interests, background knowledge, and learning abilities. By analyzing students' course selection records, grades, and other data, students' interests and potential needs can be identified, providing personalized course recommendations to improve their learning interests and satisfaction.

Teaching quality evaluation: Data mining algorithms can help educational managers objectively and scientifically evaluate teaching quality. By analyzing data such as teachers' teaching records, students' academic performance, and course evaluations, problems and deficiencies in the teaching process can be identified, providing a basis for educational managers to improve teaching quality.

Optimization of educational resources: Data mining algorithms can help educational managers optimize the allocation of educational resources. By analyzing students' course selection records, course satisfaction, and other data, it is possible to discover the popularity of courses and students' needs, thereby providing educational managers with a basis for reasonable adjustment of course settings, teacher allocation, and other resources. There are many tools for data mining, but it is a process that only closely integrates the technology provided by data mining tools with the needs of enterprises. Only by constantly running in during the implementation process can success be achieved. When choosing data mining tools in vocational colleges, multiple factors should be comprehensively considered, such as the capability to resolve difficult issues, operational performance, and data access ability.

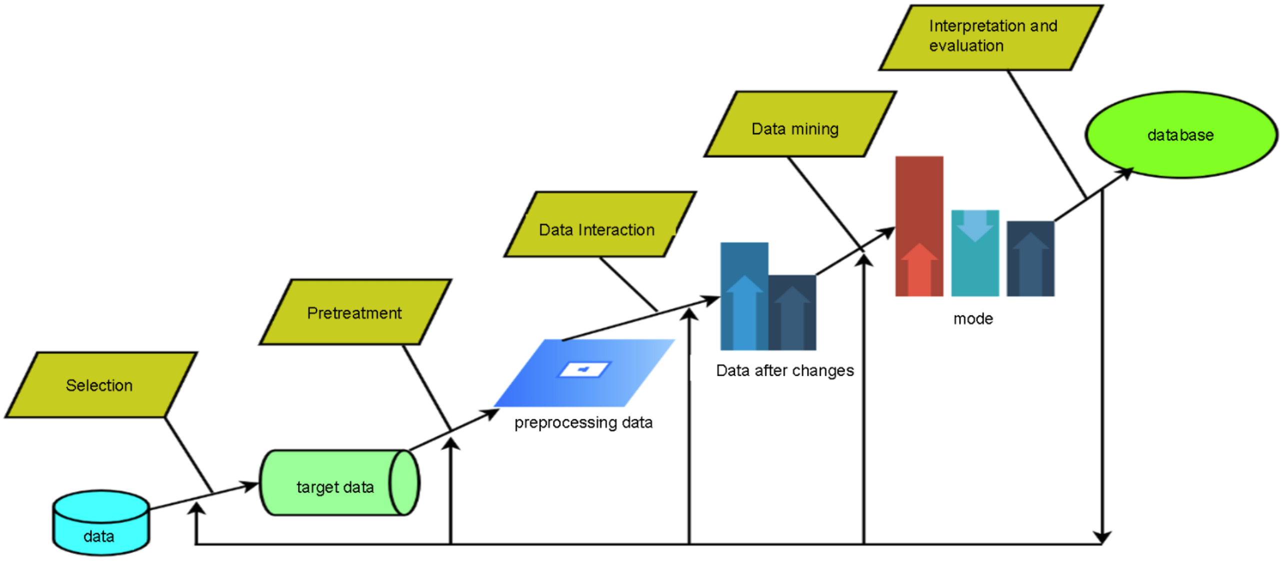

Fig. 1. Data mining process model.

Fig. 1 shows the data mining process model. In the entire data mining process, the most significant aspect is data preparation. This stage can be further divided into three sub-steps: data selection, data preprocessing, and data transformation. Data collection mainly involves finding all internal and external data information related to business objects and selecting data suitable for data mining applications. Data preprocessing involves deep processing of the extracted data to meet the needs of data mining, laying the foundation for subsequent analysis, and determining the type of mining operation to be carried out. The main job responsibilities include checking spelling errors, eliminating duplicate records, completing incomplete records, deriving missing data, completing data type conversions, and more. The data conversion process is to convert the data into an analytical model, which is established for mining algorithms. The main goal is to identify truly useful features from the initial features in order to reduce the number of features or variables that need to be considered in data mining.

B. Research on the Application of Data Mining Algorithms in the Field of Education

The application of data mining in the field of education has become an important direction of educational research. Through data mining technology, valuable information and knowledge can be extracted from a large amount of educational data, providing an important basis for educational decision-making. The learning behavior of students can be examined through data mining. By mining students' learning behavior data, it is possible to discover their learning patterns, understand their learning habits and preferences, and provide support for personalized teaching. For example, by analyzing students' behavior data on online learning platforms, it is feasible to discover their learning paths, understand their learning progress and difficulties, and provide personalized learning suggestions and assistance to students. Data mining can be used for evaluating teaching effectiveness. By mining teaching data, the efficacy of teaching methods and strategies can be evaluated, providing a basis for teaching reform. For example, the effectiveness of teaching methods can be evaluated by analyzing student performance data.

C. K-Means Algorithm

The K-means algorithm is a traditional unsupervised clustering algorithm based on distance. Finding the number of clusters and the centers of each cluster is the first step in the main concept. Then, each data point is assigned to the nearest cluster center. When all of the data points are assigned, it is the step to recalculate the center of each cluster and perform iterative calculations until the change in the cluster center is small or no longer changes. Excellent clustering results should meet the requirement that data points within the same cluster have high similarity in various attributes. In contrast, data points between different clusters have low similarity in various attributes. Definition 1 Sample Set X: Assuming there is a sample set X in a certain space, which contains m attributes and a total of n samples, A sample can be represented by Xi, and an attribute of a sample can be represented by Xit, with i ranging from 1 to n and t ranging from 1 to m. Definition 2 center point set C: Assuming there are K center points $\{c_1, c_2, \dots c_k\}$. The range of K is 1 to n, and a certain center point is represented by Cj, where the range of j is 1 to k. Definition 3: Euclidean distance: Euclidean distance is the linear distance between points in space. For example, the calculation formula from a sample point Xi to a center point Cj is shown in Eq. (1):

$$dis(x_i, c_j) = \sqrt{\sum_{t=1}^{m} (xit - cjt)^2} \quad (1)$$

Definition of MeanShift algorithm-related knowledge:

Definition 1 Sample Set X: Assuming there is a sample set X in the space, a certain sample point can be represented by Xi, and there are k such sample points. Definition 2: Region set S_h: Region set S_h represents a multi-dimensional spherical space formed by taking a point x in space as the center of a circle and then drawing a multi-dimensional circle with h as the radius. Sample set X is a collection of all data points in a region set. S_h can be represented by Eq. (2):

$$S_h = (xi|(xi - x)(xi - x)^T) \quad (2)$$

The definition form of the MeanShift vector is shown in Eq. (3):

$$M_h(x) = \frac{\sum_{xi \in Sh}(xi - x)}{k} \quad (3)$$

In Eq. (3), xi is a sample in sample set X, x is the center of the region set, and k is the number of sample points. However, in Eq. (3), the MeanShift vector has shortcomings: within the S_h region, each point plays a different role in the sub-center point. The role it plays is related to the distance between each point and the sub-center point, so improvements can be made to address this drawback.

IV. Research on the Correlation between Positive Psychological State and Academic Performance of Vocational College Students

A. Basic Situation of Psychological Health Level of Vocational College Students

To understand the mental health level of adolescent students, descriptive statistics were used to analyze the scores of ten factors in SCL-90. The results are shown in Table I. Secondly, screening was conducted on single factor scores $\geq 2, \geq 3, and \geq 4$ to obtain the rate at which mental health issues is detected (see Table II).

Firstly, according to Table I, among the SCL-90 factors, the mean of obsessive-compulsive symptoms is the highest, at 2.15 points. Rank the scores in descending order: obsessive-compulsive symptoms (2.15)>interpersonal sensitivity (1.87)>depression (1.73)>hostility=paranoia (1.72)>anxiety (1.67), terror (1.44)>somatization (1.43). The average total score of SCL-90 is 1.69, indicating that most of the student's mental health levels are normal, but they should not be underestimated for students who measure their psychological status.

TABLE I. The Overall State of Students' Mental Health in Vocational Colleges

Factor	Minimum value	Maximum value	Mean	Standard Deviation
Somatization	1	4.33	1.4	0.52
Obsessive-compulsive disorder	1	4.60	2.0	0.69
Sensitivity to interpersonal relationships	1	4.78	1.8	0.76
Depressed	1	4.62	1.7	0.67
Anxious	1	4.40	1.6	0.62
Hostile	1	5.00	1.7	0.78
Terror	1	4.43	1.4	0.52
Scl-90 total score	1	4.41	1.6	0.54

TABLE II. Detection Rate of Mental Health Problems among Vocational College Students

Factor Somatization	Factor Score⩾2		Factor Score⩾3		Factor Score⩾4	
	Number of people	*Percentage*	*Number of people*	*Percentage*	*Number of people*	*Percentage*
Compulsive symptoms	40	13.25 %	5	1.66 %	2	0.66 %
Sensitivity to interpersonal relationships	169	55.96 %	34	11.26 %	7	2.32 %
Depressed	112	37.09 %	25	8.28 %	9	2.98 %
Anxious	82	27.15 %	17	5.63 %	4	1.32 %
Hostile	72	23.84 %	14	4.64 %	3	0.99 %
Terror	92	30.46 %	25	8.28 %	8	2.65 %
Factor	45	14.90 %	5	1.66 %	1	0.33 %
SCL-90 Total score	69	22.85 %	12	3.97 %	1	0.33 %

B. Regression Analysis of Positive Psychological Capital of Vocational College Students on their Mental Health Level

Regression analysis can reveal the quantitative relationship between positive psychological capital (such as confidence, hope, resilience, optimism, etc.) of vocational college students and their mental health level. This analysis not only helps to understand which psychological capital factors are more important, but also predicts what range a student's mental health level may be in given levels of psychological capital. Confidence refers to an individual's affirmation of their abilities and values. Regression analysis can help us understand how hope affects mental health, such as whether students with stronger feelings of hope exhibit fewer symptoms of anxiety or depression. The method of gradually entering variables is used, with each dimension of psychological capital as the independent variable and the total score of SCL-90 as the dependent variable. Table IV represents the results of the multiple regression analysis that was performed on the variables.

TABLE III. REGRESSION ANALYSIS RESULTS OF POSITIVE PSYCHOLOGICAL CAPITAL ON MENTAL HEALTH LEVEL

Order	Entering variables	R2	F	B	SE	β	T
1	Toughness	0.208	78.679	-0.255	0.029	-0.456	-8.870***
2	Toughness	0.259	52.269	-0.179	0.033	-0.319	-5.495***
	Optimistic			-0.118	0.026	-0.264	-4.549***

***P＜0.001

From Table III, it can be seen that psychological resilience and optimism enter the regression equation, with resilience entering first, indicating that psychological resilience has the greatest predictive effect on mental health levels by predicting 20.8% of variables. The combined predictive power of psychological resilience and optimism is 25.9 percent. Hope and self-efficacy did not enter the regression equation. For mental health, the total score is 1.69, indicating that there are little or no psychological symptoms, but their occurrence is not frequent. The most prominent symptom among various factors is obsessive-compulsive disorder, with a mean score of 2.15, indicating that students attending vocational colleges experience mild to moderate degrees of this symptom. Impulses and thoughts are examples of compulsive symptoms that repeatedly invade an individual's daily life, and they are able to experience that they, themselves, are the source of these impulses and thoughts despite being aware of their meaninglessness. Although they resist vigorously, they are still unable to control them. The first reason for this is that students have high demands on themselves. They have been facing overly strict education from their families and schools since birth and must comply with regulations and orders. Otherwise, they will be denied, belittled, or even scolded by parents and teachers, as well as ridiculed by peers. Over time, these rules will be internalized into their strict standards. Secondly, students face negative emotions such as grievances, fears, anxiety, and depression that they experience in their emotions, learning, and interpersonal relationships, coupled with a lack of skills to express themselves directly through language or obtain satisfaction through appropriate behavior, making it difficult for them to rely on their own demands and external environment.

Environmental review. So, it transforms into symptoms of thought, emotion, and behavior and becomes compulsive symptoms through self-suppression. There were no significant differences in the analysis of psychological health factors among vocational college students from four aspects: gender, place of origin, and whether they are only children or are in single-parent families. However, the research results show that girls score significantly higher than boys in the dimension of terror, indicating that girls are more susceptible to psychological distress caused by terror. Psychological development is related to the education provided by family, school, and society. In many people's minds, there is a stereotype of girls, believing that they are not as good as boys in higher vocational education, especially in subjects such as mathematics, physics, and chemistry. Simultaneously, girls tend to experience tension, anxiety, and unease due to the mounting pressure of appearing for college entrance exams, and their fear will become apparent. Given that girls are more delicate and sensitive than boys, from the standpoint of evolutionary psychology, it is especially crucial to pay attention to their inner experiences and offer guidance on girls' mental health. The positive orientation of students' psychological capital in all dimensions$dimension\ score \geq 4$), $hope\ (57.95\%) > optimism\ (53.64\%) > resilience\ (35.43\%) > self-efficacy\ (28.48\%)$, indicates that more than half of students have more optimistic positive psychological capital. The highest scores for resilience and self-efficacy were in the range of 3 to 4, with resilience scoring 57.62 percent and self-efficacy scoring 63.58%. This indicates that vocational college students are in a general state in these two dimensions. Many students in traditional teaching methods have poor learning and personality development and need more successful experiences, which may affect their self-efficacy. Other contributing factors include the single assessment and evaluation system, low teacher-student ratio, and other issues. Social support levels, academic stress, and interpersonal relationships all have an impact on how resilient students become psychologically. No significant differences were seen in the psychological capital dimensions of vocational college students from four aspects: gender, place of origin, whether they are only children and single parent families. However, in terms of self-efficacy, boys are significantly higher than girls, and the gender differences in self-efficacy are closely related to factors such as social expectations, gender role concepts, and social reality. In addition, students from non-single-parent families are more optimistic than students from single-parent families for the following two reasons. Firstly, there is a lack of emotions, as teenagers have not only material needs during their growth process but also indispensable emotional experiences from their families. Some divorced parents do not care enough about their children and do not have their children's emotional needs. Some parents, although accepting their children, do not truly take responsibility, which leads to abandonment or neglect, affecting the personality development of teenagers. Secondly, there is a bias in social evaluation, where children from single-parent families often become the focus of discussion and are criticized or even distorted, leading to students developing a sense of inferiority.

V. Model Construction Based on Data Mining Algorithms

Fig. 2 indicates the system's overall architecture, which mainly consists of five parts: control center, warning object, data acquisition, psychological analysis, and psychological warning. For college psychological warnings, the control center mainly refers to college counselors or psychological counseling institutions, who are the executors of the plan and are mainly responsible for the operation and maintenance of the intelligent warning system and the processing of student psychological abnormal warning information. The warning targets are college students. The data acquisition mainly includes a depth-of-field data acquisition module and a data preprocessing module. The former obtains and records three-dimensional data of warning objects by reading the depth of field camera port. The latter processes the obtained raw data through data mining methods and transforms the data into standard data that can be directly input into intelligent algorithms through normalization methods. The psychological analysis section mainly includes an intelligent classification module and a psychological state module. The intelligent classification module takes standardized data as input and the psychological category of the warning object as output. By fitting the relationship between the two through the powerful nonlinear approximation ability of artificial intelligence algorithms, the psychological state module achieves the conversion of psychological category data to students' psychological state. The psychological warning section is composed of an abnormal warning module, which detects students' psychological status based on the output results of psychological status data. When an abnormal state occurs, an alarm is sent to the control center for processing. Then, the control center handles the abnormal students, thus achieving a closed-loop early warning system with university students as the warning object. This structure effectively avoids the drawbacks of traditional systems centered around counselors or related institutions. It improves the initiative and timeliness of psychological early warning work in universities by focusing on students.

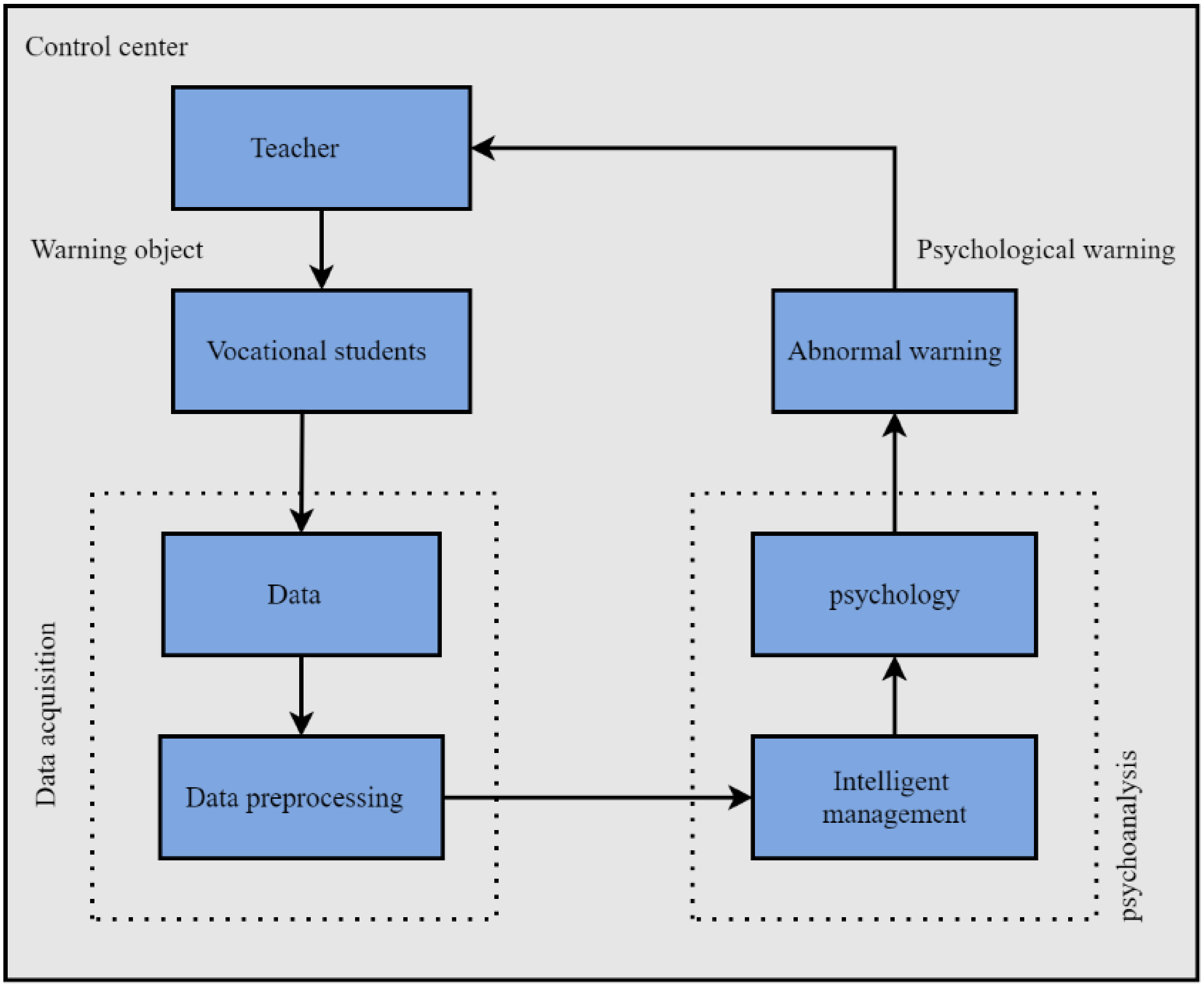

Fig. 2. Overall architecture.

A. Data Collection and Preprocessing

Due to the complexity of psychological warning problems, it is necessary to accurately extract the psychological feature data of the warning object while minimizing interference with the warning object as much as possible while considering the timeliness of data acquisition. This design uses a depth-of-field camera as the data collection device. It uses the 3D image data of the warning object in a specific area as the raw data for extracting the psychological characteristics of the warning object. In addition, in order to reduce the difficulty of data processing, this design selects the Kinect V2, a new generation somatosensory camera launched by Microsoft that currently has a relatively complete API as the data collection device. It has a high accuracy of about 2mm and has an infrared camera, making data collection possible in the case of gray and dark algorithms. By utilizing TOF technology to collect deep data, the accuracy is sufficient to identify human hand posture and even heart rate, fully meeting the requirements of psychological data extraction in this system. This article uses the official development toolkit Kinect for Windows SDK v2.0 to extract relevant data easily. The following describes the specific data acquisition and preprocessing process, as shown in Fig. 3.

B. Analysis and Interpretation of Model Results

According to the implementation process of this system, experimental verification of this design scheme was conducted in vocational colleges. Due to the particularity of the psychological abnormality warning, the recognition results of facial expression categories for the warning object in this design were verified. The validation process and results are as follows: 500 college student volunteers were selected as samples for the validation of this system. 300 of them served as the training set for the BP neural network, with each volunteer creating six types of facial expressions and using Kinect V2 to obtain training after data preprocessing, data is inputted into the neural network for training, and the remaining 200 volunteers are the test set of the scheme. The classification results of the trained BP neural network for six facial expressions in the test set are presented in Table IV.

From Table IV, it can be seen that the BP neural network designed in this article has a recognition rate of 79% for complex expressions such as expressions 4 and 6 in the recognition of facial expression states of warning objects. The overall average recognition rate is 88.6%, and the error rate is 2.3%. It can meet the needs of psychological warning and also verify the effectiveness of this system.

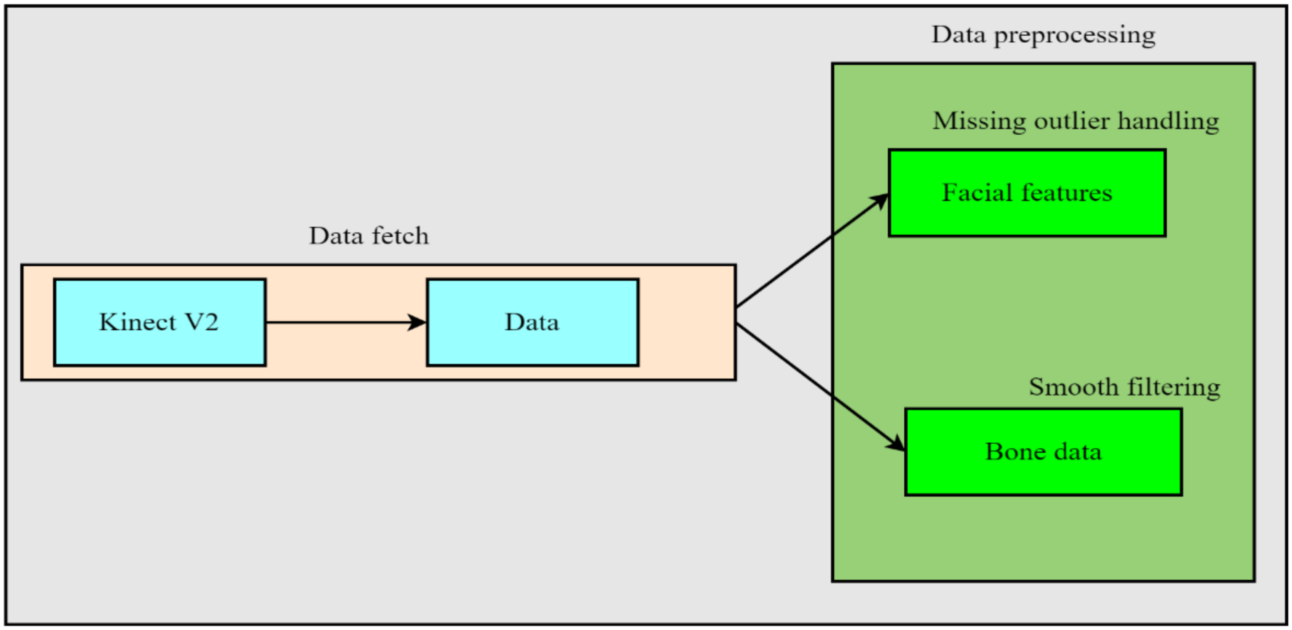

Fig. 3. Data acquisition and processing framework diagram.

TABLE IV. BP NEURAL NETWORK RECOGNITION RESULTS

Number	1	2	3	4	5	6
Recognition frequency	200	200	200	200	200	200
Successfully identified	192	195	180	168	173	159
Unrecognized	8	4	18	27	22	31
Misidentification	0	1	2	5	5	10
Recognition rate	96%	97%	90%	84%	86%	79%

VI. Discussion

This study explores in depth, the correlation between student psychological state and academic performance through the application of data mining algorithms. The results reveal a significant correlation between the two, providing a new perspective for us to understand the learning process and psychological development of students. The stability and positivity of psychological state have a significant positive impact on the improvement of academic performance, and vice versa. This discovery emphasizes the importance of mental health in the learning process of students.

Comparing the results of this study with existing theories, we found that they have some extent support relevant theories in cognitive psychology and educational psychology. For example, according to the theory of emotional regulation, the psychological state of students can affect their learning strategies and effort levels, thereby affecting their academic performance. The results of this study are consistent, indicating that psychological state is indeed one of the important factors affecting student academic performance.

Understanding the correlation between student psychological state and academic performance is of great guiding significance for educational practice. Educators can provide personalized support and intervention based on the psychological state of students, helping them adjust their mentality, enhance their learning motivation, and thus improve their academic performance. In addition, this also helps us to evaluate students' academic performance more comprehensively, not limited to a single performance indicator.

VII. Conclusion

This article explores the construction of a correlation model between the positive psychological state and academic performance of vocational college students based on data mining algorithms. An effective method suitable for the field of education has been discovered through analysis of existing data mining tools and algorithms. In the data preparation stage, data was collected, preprocessed, and transformed to meet the needs of data mining better. In the algorithm application stage, a detailed discussion was conducted on the application research of data mining algorithms in the field of education in order to find an effective method to predict the relationship between students' positive psychological state and academic performance. Through in-depth research on data mining algorithms in the field of education, vocational colleges have discovered some interesting results. A significant correlation was found between students' positive psychological state and academic performance. This means that students' psychological state during the learning process has a significant impact on their academic performance. Therefore, educators should pay attention to students' mental health in order to improve their academic performance. Data mining algorithms have broad application prospects in the field of education. By mining students' learning data, educators can better understand their learning needs and difficulties and thus develop more effective teaching strategies. In addition, data mining algorithms can also help school managers identify potential problems, such as students' mental health issues, academic misconduct, etc., and take corresponding measures to intervene. How to combine data mining algorithms with other educational technologies to enhance education quality, way of using data mining algorithms to predict students' future academic performance, and provide personalized learning suggestions for students. The resolution of these issues will bring more innovation and development to the field of education. By constructing a correlation model between the positive psychological state and academic performance of vocational college students based on data mining algorithms, a new research method is provided for the field of education. With the continuous development and improvement of data mining technology, it will become more and more significant in the field of education, making greater contributions to enhancing the quality of education and promoting educational equity.

However, there are certain limitations to the research. When collecting data, we may rely on self-report methods such as questionnaire surveys and online tests, which may lead to subjectivity and bias in the data. In addition, some important psychological state indicators may be difficult to quantify or accurately measure, thereby affecting the accuracy and reliability of the model. In future research, we need to fully consider these limitations and take corresponding measures to improve and perfect research methods, in order to more accurately reveal the relationship between psychological state and academic performance, and provide more scientific and effective decision support for educational practice.

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Physical Training in Higher Vocational Colleges Based on Sequencing Adaptive Genetic Algorithm

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***Abstract*—This study is based on the sequencing adaptive genetic algorithm and conducts an in-depth discussion on optimization issues in the field of higher vocational sports training. By analyzing the shortcomings of traditional genetic algorithms in optimizing training plans, a new sequencing adaptive genetic algorithm is proposed to improve the optimization effect and adaptability of training plans. First, the optimization goals and constraints in higher vocational sports training were studied, including the diversity of training content and the rationality of training intensity. Secondly, based on the sequencing adaptive genetic algorithm, an optimization algorithm framework suitable for higher vocational sports training was designed, including key steps such as individual coding, fitness evaluation, and crossover mutation. Then, the proposed algorithm was verified and analyzed using experimental data. The results showed that the algorithm can effectively improve the optimization effect of the training plan and has strong adaptability and generalization capabilities. Finally, through comparison with traditional genetic algorithms and other optimization algorithms, the superiority and practicability of sequencing adaptive genetic algorithms in higher vocational sports training are further verified.**

Keywords—Sequencing adaptive genetic algorithm; higher vocational colleges; sports training; convergence speed

I. Introduction

With the continuous optimization and improvement of vocational education, higher vocational academic education has received more and more attention [1]. On the one hand, the cultural education of higher vocational colleges is further enriched. Still, on the other hand, the lack of physical education and training in HVC is relatively weak. For high-quality students, it is the embodiment of cultural ability and the improvement of physical quality [2], [3]. From the perspective of practicality, the physical training and education of HVC can be carried out to cultivate students' physical fitness, exercise their will, improve students' abilities from many aspects, and give play to the multiple effects of higher vocational education, the characteristic training advantages of HVC [4].

However, it is worth noting that, how to set up physical education classes in HVC and arrange them to combine work and rest, which can exercise physical fitness and relax better. In response to this problem, scholars have proposed many methods, such as introducing basic genetic algorithms, trying to change the problems of slow convergence and poor stability, and avoiding the two-level differentiation [5]. Still, the basic genetic algorithm has certain application limitations. Therefore, some scholars further optimize, introduce the genetic algorithm's incorporation of co-evolution, conduct competition among multiple courses to improve global convergence, and achieve the optimization balance of multiple courses. However, this is prone to weakening and degradation [6], [7]. Physical training in higher vocational colleges is one of the important ways to improve students' physical quality and sports skills, its purpose is to cultivate students' physical quality, improve athletes' competitive level, and promote the overall development of students' physical and mental health. The traditional training methods of higher vocational sports are often subject to the design and implementation of training plans, and there are problems such as unstable training effect and low degree of individuation, so it is necessary to introduce more scientific and effective optimization methods to improve training effect. Genetic algorithm is a common heuristic optimization algorithm in the research field of optimization problems, which has strong global search ability and adaptability. In recent years, with the continuous development and improvement of genetic algorithm, sequencing adaptive genetic algorithm, as a variant of genetic algorithm, has been widely concerned and has achieved some successful applications in many fields. Sequencing adaptive genetic algorithm is an optimization method based on population evolution. Its basic idea is to continuously select individuals with higher fitness from the initial population to solve the optimization problem by simulating the selection, crossover and mutation operations in the process of biological evolution. Compared with traditional genetic algorithms, sequencing adaptive genetic algorithm has stronger adaptability and flexibility in individual evaluation and selection, crossover and variation, and can better cope with the solving needs of different problems. In the field of higher vocational sports training, optimizing the training plan is the key to improve the training effect and individuation degree. The traditional training plan design usually relies on experience and professional knowledge, and it is difficult to fully take into account the characteristics and needs of different athletes, so it is necessary to introduce more scientific and effective optimization methods to improve the design of training plans. As a new optimization method, sequencing adaptive genetic algorithm has good application potential and development prospect, and can provide new ideas and methods for the improvement and promotion of physical training in higher vocational colleges.

In summary, as a new optimization method, sequencing adaptive genetic algorithm has the potential and prospect of application in the field of higher vocational sports training, but the relevant research is still relatively limited, and its specific application and effect in this field need to be further discussed.

The field of higher vocational sports training has made some progress in recent years, including the improvement and innovation of training methods, the improvement of athletes' technical level, and the quantitative evaluation of training effects. With the development of sports science and the advancement of technology, more and more scientific methods and technologies are introduced into higher vocational sports training, making the training process more scientific and personalized. However, the field of higher vocational sports training still faces some challenges. This includes the optimization of training plans, the satisfaction of athletes' personalized training needs, and the quantitative evaluation methods of training effects. Traditional training methods may not fully take into account the characteristics and needs of different athletes, resulting in unsatisfactory training results. There are still some unresolved issues in the field of higher vocational sports training, such as how to better realize the personalization and differentiation of training plans, how to improve the accuracy and scientificity of evaluation of training effects, how to effectively adjust and Optimize training plan, etc. Solving these problems will help improve athletes' training effects and competitive levels. This study is based on the sequencing adaptive genetic algorithm and focuses on the optimization problems in higher vocational sports training. Compared with traditional training methods, sequencing adaptive genetic algorithms are more personalized and adaptable and can better meet the training needs of different athletes. The importance of this study is that by introducing new algorithmic methods, it improves the optimization effect and degree of personalization of the training plan, and provides new ideas and methods for the improvement and improvement of higher vocational sports training. At the same time, this research also fills the gap in optimization methods in the field of higher vocational sports training, and is innovative and advanced to a certain extent.

Based on this, the article relies on the sorting adaptive genetic algorithm through the introduction of adaptive genetic operators so that each course has its cross arrangement, and it is gradually tried and automatically changed, aiming to adjust the optimal sports training in HVC.

Section I briefly introduces the background and significance of physical training in higher vocational colleges, discusses the problems and challenges existing in physical training in higher vocational colleges, and puts forward the purpose and significance of this research; Section II analyzes the present situation of PE teaching in higher vocational colleges; Section III discusses the relationship between higher vocational education and physical training. Section IV proposes the exercise training based on adaptive genetic algorithm; Section V determines the research object and data source of the experiment, and describes the experimental design and setting, including participant selection, experimental conditions, evaluation indicators, etc. Discussion is given in Section VI. Finally, the main findings and contributions of this study are summarized, the direction and suggestions for further research are put forward, and the application prospect of sequencing adaptive genetic algorithm in higher vocational sports training is prospected in Section VII.

II. An Analysis of the Current Situation of Physical Education in Higher Vocational Colleges

A. *Physical Education Teaching Goal*

The so-called PE is not only simple sports such as long-distance running and hurdles, but also actively guides students, such as adding group gymnastics, Tai Chi, and other sports, integrating traditional culture and sports, and guiding students in team spirit, Physical and mental health, and other aspects have been fully displayed and embodied.

B. *Physical Education Teaching Methods*

Concerning the approach of physical education, the traditional methods are led by teachers, imparting the corresponding knowledge to students, and it is difficult for students to choose according to their interests. The consequence is that the development of all students cannot be satisfied, making physical education teaching quality cannot be significantly improved [8], [9].

C. *Physical Education Content*

At present, physical education courses and physical training are mostly based on exercise methods. On the one hand, physical training with a large amount of exercise may only suit some students. On the other hand, repeated courses will be produced, which are only continuously strengthened. Over a long period, students will become tired of learning, leading to a continuous decrease in the quality of teaching.

D. *The Need for Constructing Special Sports Courses in Higher Vocational Colleges in the New Era*

Different HVCs have different school-running ideas and concepts, and their characteristics are also different. Therefore, higher vocational physical education curricula and physical training should also be their focus [10]–[13]. Quality education can be introduced and integrated with the physical education courses of HVC, guide students to conduct comprehensive development training, comprehensively cultivate all aspects of quality, complement cultural courses, and finally realize the high-quality sports training and cultivation of HVC.

E. *The Need of Physical Education Reform in Higher Vocational Colleges*

Given the traditional teaching methods, teaching goals, and teaching content, traditional methods need to be reformed, which is mainly reflected in (1) ideological reforms to guide students’ independence and innovation, comprehensively considering students’ intelligence and other factors to develop and integrate Quality education is expanded to cultivate students with good habits and good ideas; (2) Reform of the model, change the traditional teacher teaching, students passively accept teaching, guide the gradual participation of academics, full participation, from the beginning of the physical training design and implementation, Give full play to individual initiative and creativity, assisted by teachers, and cooperate; (3) Reform in methods. From the perspectives of thinking mode and physical instinct, carry out effective sports training guidance, complete the concept change and plan formation, and raise the standard of instruction; (4) Reform in evaluation. Transform from traditional evaluation indicators to comprehensive evaluations of students’ progress, physical fitness, sports skills, and learning attitudes to guide students' physical and mental health.

III. Higher Vocational Education and Sports Training

A. The Content of Physical Education in HVC aiming at Quality Education

For physical education and training in HVC, it is necessary to fully consider the feasibility and integration of quality education in teaching content, fully integrate market needs and teaching, and arrange the content and training of teaching scientifically, effectively, and reasonably [13], [14]. The goal of its teaching is to enhance the physical fitness of students and cultivate comprehensive graduates. Therefore, in addition to traditional sports, it is necessary to add or set up some new sports training content according to the local characteristics of the advantages of the school, such as Tai Chi, Boxing, group gymnastics, swimming, etc.

B. Carry out Physical Education Based on Students' Professional Characteristics

The PETs and resources of higher vocational colleges are different. Therefore, in addition to traditional physical training, it is necessary to design the division of labor according to the existing profession. Teaching physical education requires a thorough understanding of the factors that affect the students, designing teaching content that aligns with students' interests and sports, and conducting practical sports training to improve students' physical fitness and effectively give full play to physical education in HVC. The role of quality education in students' life is very important.

At the same time, different sports training courses and contents are set up for the student subjects of different majors in HVC. It is optional for all students to make a unified selection. According to the characteristics of different majors and occupations when selecting courses, they are classified and pushed and selected separately to ensure that there are Course selection is required to ensure that the selection is more scientific, reasonable, and effective.

To continue the physical education process of higher vocational colleges from inside to outside, HVC should investigate the combination of extracurricular physical activity and intramural physical education to form a unity of teaching and practice to ensure the unity of students inside and outside the campus to the greatest extent and completeness, but also to ensure the connection between HVC and enterprises.

C. Physical Education Teaching Form That Highlights Practical Ability

The higher vocational college's PE should highlight students' practical abilities. Simulating professional scenes and social situations, physical training, and future work abilities should conduct comprehensive training. According to different majors, different genders, and different interests, they are separately cultivated. Design different physical education or physical training content to reserve enough knowledge of physical education for students. At the same time, students experience different roles in sports training, such as referees, athletes, captains, etc., to fully exercise their resilience and unity ability, and they can also exercise other abilities while exercising. At the same time, by simulating the requirements of the enterprise, it is required not to be late or leave early and to attend sports training fully.

IV. Sports Training Based on Adaptive Genetic Algorithm

In adaptive Genetic Algorithms Based on Co-evolution (SAGA) based on co-evolution, in each iteration of the algorithm, the evolution process and the collaborative process are carried out in sequence [15], in which the evolution process uses adaptive genetics. With a strong global search capability and a good convergence speed, the SAGA algorithm's genetic operation seeks to improve the genetic algorithm from both local and global perspectives.

The objective function is the core indicator in the genetic algorithm (GA) optimization process. It defines the goals or performance evaluation criteria that need to be optimized. In the scenario of higher vocational sports training, the objective function may be diverse, such as the overall performance index of the training plan, the athlete's training effect evaluation index, etc., which are determined according to the specific content and purpose of the research. Generally speaking, genetic algorithms can be used for optimization problems as well as search problems. In optimization problems, genetic algorithms find optimal solutions or near-optimal solutions through iterative evolution; while in search problems, genetic algorithms are used to find solutions that meet specific conditions in a large-scale search space. In the scenario of higher vocational sports training, if it is a training plan optimization problem, the genetic algorithm is used to optimize the objective function, that is, to find the best training plan; if it is a training plan design problem, the genetic algorithm is used Search for the optimal training plan.

A. Framework Description of Co-Evolution

The two-layer co-evolutionary framework is shown in Fig. 1. The population is separated into n sub-populations. Enhanced co-evolution is employed to prevent early maturation within the populations. The phenomenon continues to uphold the global search capability. The local population forms the lower layer, and a neighborhood-based local adaptive evolution algorithm is applied for conducting the local lookup. Enhancing convergence speed and promptly locating the best local solution are the goals. The local population is promoted to the top performers in the global group through the promotion operation association between the two layers. Subsequently, the local adaptive algorithm converges to the local optimum quickly.

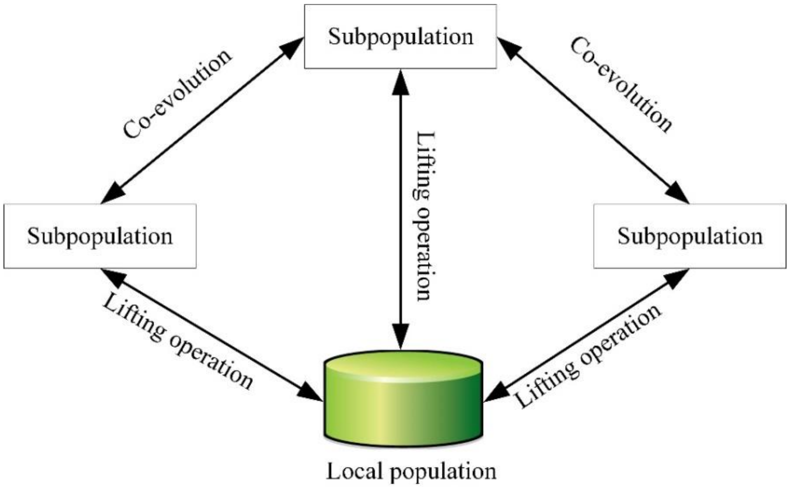

Fig. 1. Two-layer framework model diagram of co-evolution.

B. Adaptive Mutation Strategy of Local Evolution

The lifting operation concentrates the better individuals between the n subpopulations of the world and local populations. The local evolution uses a neighborhood-based local adaptive evolution algorithm to rapidly allow the local population to converge to the ideal solution. In this algorithm, selection and crossover operations are not used; only mutation operations are used, and the mutation rate that adapts is employed. The mutation is restricted to the individual's Δ neighborhood, and the purpose is to accelerate the convergence speed of the local population. The adaptive mutation rate among them is described as follows:

$$P_m(t) = 0.01 + NG \times cof \quad (1)$$

Of them, t denotes the algebra of the current iteration, and NG denotes the algebra for which there hasn't been a better solution since the last generation, at which point an excellent solution first surfaced. Typically, a small value, like 0.01, is used to determine the threshold for a coefficient called cof, which increases the mutation rate.

Formula (2) illustrates that if the evolution process is smooth—if a better solution emerges in every generation—then NG=0. In this case, it can be concluded that the current mutation operation effect is preferable, and raising the mutation probability is unnecessary. If it has not evolved, the longer the time will be. The greater the NG, the higher the mutation probabilityP_m, and the need to expand the search range, but once a particular threshold for the number of non-evolved generations is reached (if cof=0.01, the threshold is 100 generations), then $P_m = 1$ can be considered as the population at this time There is no better solution in the 4-neighborhood, and the evolution process is terminated.

C. SAGA Algorithm Description

Through the analysis of the above two-layer framework and operation strategy, the steps of the adaptive algorithm based on co-evolution (SAGA) are described as follows:

1) Perform a random initialization on the global population and set the population to n;

2) Improve the algorithm of the sub-population and form the coverage of the global population;

3) For the local adaptive evolution, the formation of a new population is optimized;

4) Cooperate based on the new population to achieve continuous improvement;

5) If the termination conditions are met, then end. Otherwise, go to (2).

Chromosomes are usually represented by bit strings, where each bit represents the value of a gene or variable on the chromosome. The following is a simple example. Suppose there is a chromosome containing 5 genes, and each gene has 2 possible values (0 or 1). The chromosome can be represented as a 5-digit bit string, for example: 10110.

In genetic algorithms, crossover and mutation are two common genetic operations used to generate new individuals. Their probabilities are usually specified by the user during algorithm design.

The crossover operation partially exchanges the chromosomes of two parent individuals to produce new offspring individuals. For example, for chromosomes represented by bit strings, crossover can cut the two chromosomes at random positions and swap the parts after the cut point. Suppose there are two parent individuals A and B, respectively 10110 and 01101, then the possible offspring individuals are 10101 and 01110. The probability of the crossover operation is usually specified by the user and is generally set between 0.6 and 0.9; the mutation operation randomly changes the values of some genes in the individual chromosomes to introduce new changes and diversity. For example, for a chromosome represented by a bit string, a mutation could randomly invert certain bits in the chromosome. Suppose there is a chromosome 10110, which may become 10100 after mutation. The probability of mutation operations is usually low and is generally set between 0.001 and 0.01. It should be noted that the probability of crossover and mutation can be adjusted according to specific problems and experimental experience. Certain experiments and tuning are usually required to determine the best parameter settings.

V. Experimental Verifications

According to the dual consideration of the majors studied by the students of HVC and their future occupations, the student's physical fitness requirements are integrated, and the focus is on selecting courses to improve their physical fitness and, at the same time, related skills. The specific physical education training is shown in Fig. 2.

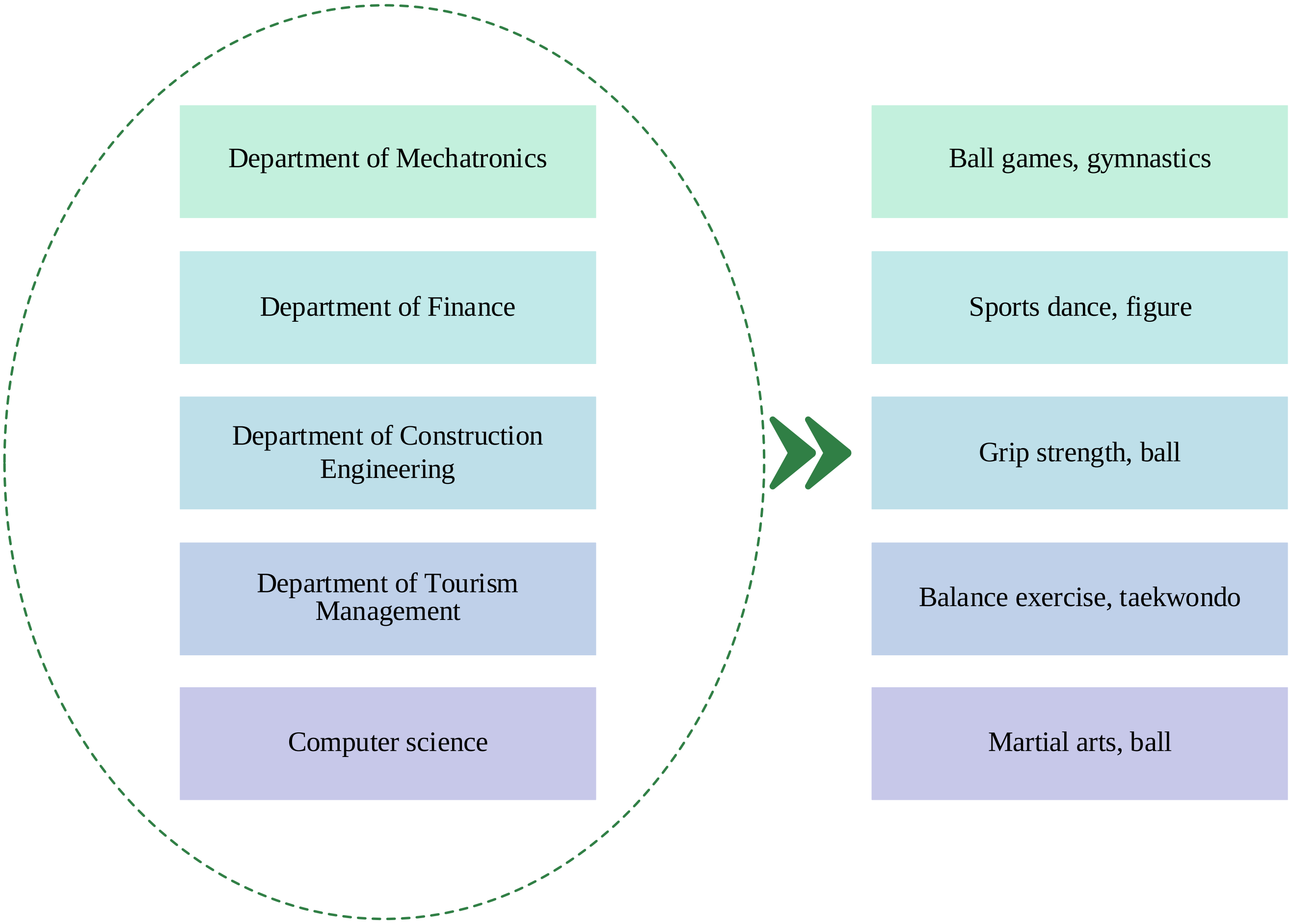
Department of Mechatronics
Department of Finance
Department of Construction Engineering
Department of Tourism Management
Computer science
Ball games, gymnastics
Sports dance, figure
Grip strength, ball
Balance exercise, taekwondo
Martial arts, ball

Fig. 2. Practical physical education curriculum in higher vocational education.

To further clarify the effectiveness of the SAGA algorithm, this paper uses this method, the ECCGA algorithm, and the FLAGA algorithm to optimize the performance of the physical education curriculum setting. The relevant parameters are set as follows: the physical education class hours are set to 240, divided into three sample groups, respectively 90, 80, and 70. The probability of coordination is set to 0.42. m is set to 4, the environmental load K is set to [80, 80, and 20], and the probability of promotion is set to 0.4, so the selected test function is as in Formula (2), Formula (3), Formula (4) as shown in:

$$f_1 = \left| \frac{\sum_{i=1}^{n} cos^4(x_i) - 2\prod_{i=1}^{n} cos^2(x_i)}{\sqrt{\sum_{i=1}^{n} x_i}} \right|, 0 \le x_i \le 10, 1 \le i \le n, \prod_{i=1}^{n} x_i = 0.75 \tag{2}$$

$$f_2 = \sum_{i=1}^{n} \{x_i^2 - 10\,cos(2\pi x_i) + 10\}, -5.12 < x_i < 5.12 \tag{3}$$

$$f_3 = -20\,exp\left\{-0.2\sqrt{\frac{1}{N}\sum_{i=1}^{n} x_i^2}\right\} - exp\left\{\frac{1}{N}\sum_{i=1}^{n} cos(2\pi x_i^2)\right\} + 20 + exp(1), -32 < x_i < 32 \tag{4}$$

F1 is a non-linear function, and f2 and f3 are multi-dimensional and multi-modal. It is simple to become mired in a locally optimal solution when solving. Set n to 30, then the results of a certain iterative optimization process can be obtained, as shown in Fig. 3, Fig. 4, and Fig. 5.

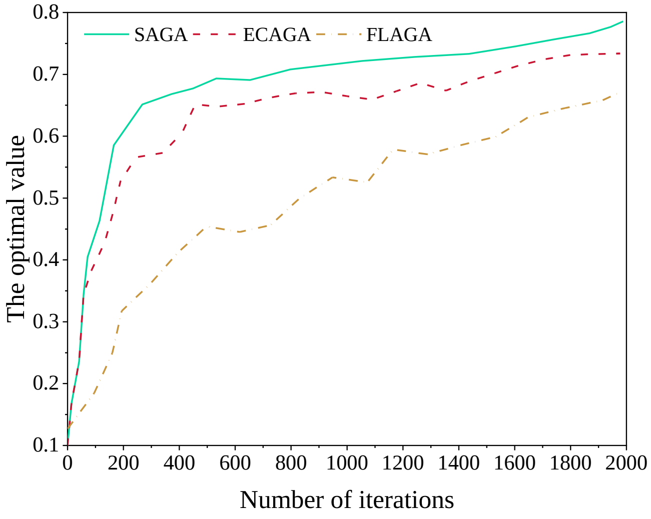

Fig. 3. Iterative process of function f1.

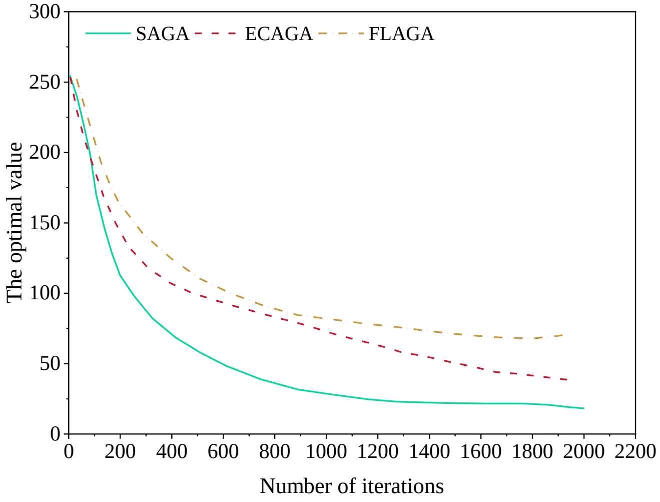

Fig. 4. Iterative process of function f2.

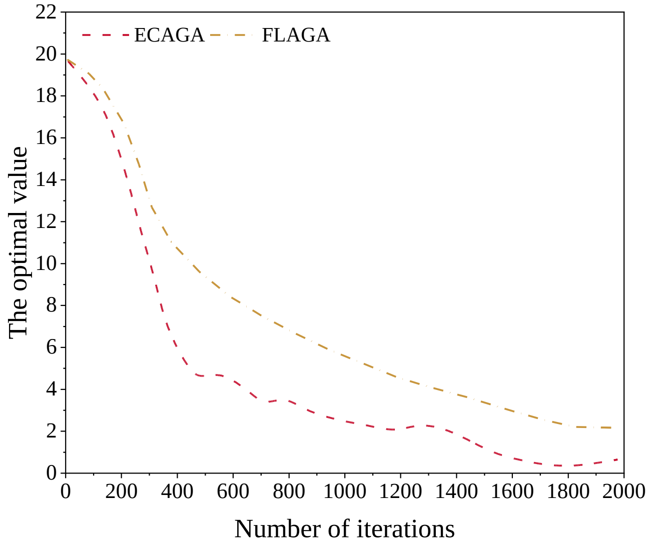

Fig. 5. Iterative process of function f3.

It can be seen from the results in Fig. 3 that it is the iterative process of the function. Compared with the other two functions, the convergence speed of the SAGA algorithm is faster and closer to the optimal value of 0.81; from the two calculation results in Fig. 4 and Fig. 5, you can see the convergence process of the SAGA algorithm has fewer fluctuations, so it can be obtained that compared to the other two algorithms, the SAGA algorithm not only has a faster convergence speed but also has a higher accuracy. Similarly, when solving the maximum value of the function value, when the SAGA algorithm is iterated 8000 times, the optimal function value 0.81 is obtained. Still, the traditional method is iterated 40,000 times more than the SAGA algorithm. Therefore, the SAGA algorithm has more obvious advantages.

VI. Discussion

The traditional training plan design is often based on expert experience and general rules; it is difficult to fully consider the individual differences and training needs of different athletes. The sequencing adaptive genetic algorithm can automatically adjust the training plan according to the characteristics and goals of each athlete to achieve personalized and differentiated training, so as to better meet the needs of athletes. Through the comparison of experimental results, it is found that the training plan optimized by sequencing adaptive genetic algorithm has certain improvement in training effect. Compared with the traditional training plan, the optimized training plan is more scientific and reasonable, and can better improve the training effect and competitive level of athletes. In this study, we adjusted and optimized the parameters of the sequencing adaptive genetic algorithm in a certain range, and compared the optimization effects under different parameter settings. The results show that the algorithm parameters have a certain influence on the optimization results, and reasonable setting of algorithm parameters can improve the optimization effect and convergence speed. Although the experimental results of this study show that the personalized training plan based on sequencing adaptive genetic algorithm has certain advantages, its feasibility and stability in practical applications still need to be further verified. Future studies can further expand the sample size and experimental scope to explore the applicability of the algorithm in different scenarios and sports. There are still some limitations in this study, such as small sample size and insufficient control of experimental environment. Future studies can further improve the experimental design, strengthen the evaluation of algorithm performance and stability, and explore more effective and reliable methods for optimizing personalized training plans.

In summary, the optimization method of higher vocational physical training based on sequencing adaptive genetic algorithm has certain potential and application prospect, but it needs further verification and improvement in practical application. We believe that with the progress of technology and in-depth research, this method will bring more innovations and breakthroughs in the field of higher vocational sports training.

VII. Conclusions

As a group of important academic institutions for cultivating skilled students, vocational colleges are receiving more and more attention. The students who are trained should also integrate academic and practical skills to improve the physical fitness of students. This article uses a ranking adaptive genetic algorithm. As a basis, it has absorbed the advantages of strong convergence and put forward an adaptive genetic algorithm to protect sports training and the algorithm's stability on time, which is advantageous to setting sports courses in HVC and has obvious effects.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest

FUNDING STATEMENT

Not applicable.

AUTHORSHIP CONTRIBUTION STATEMENT

Quanzhong Gao: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

DECLARATIONS

Not applicable

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Packaging Beautification Design Based on Visual Image and Personalized Pattern Matching

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***Abstract*—Visual image technology is widely used in the field of product art design, enriching the visual beautification design effect of products. To improve the design effect of product packaging, a personalized packaging pattern matching technology is proposed based on computer vision image technology. Firstly, based on user needs, a pattern feature extraction technology is proposed, which uses the total variation model and GrabCut model to smooth and segment the image. Secondly, an improved style transfer generative adversarial network model is proposed for transfer training between feature elements and targets. Considering the problem of insufficient detail preservation in traditional transfer models, attention layers are incorporated into the transfer model for improvement. In the pattern feature extraction experiment, the proposed model had the best pixel accuracy in Image 1. In the pattern matching experiment, the proposed model had the lowest mapping loss in both pattern combinations, with a value of 0.135 in the Zhuang brocade pattern and 0.236 in the blue and white porcelain pattern, which was superior to other models. Comparing the effect of different model pattern combinations, in the blue and white porcelain pattern combination, the proposed model had an optimal peak signal-to-noise ratio of 32.32, which was superior to other models. The proposed model has excellent application effects in packaging design beautification. The research content will provide critical technical references for e-commerce product packaging design and intelligent image processing.**

Keywords—Visual images; personalized patterns; total variational model; GrabCut model; migration model

I. Introduction

Visual image technology is a technique that processes and analyzes images through computers. This includes image recognition, image processing, and image generation. Visual image technology is widely applied in multiple fields, such as medical image analysis, security monitoring, intelligent transportation, etc. [1]. In product packaging design, visual image technology can be used to enhance the design effect of packaging, making it more attractive to consumers [2]. Pattern packaging design refers to the use of various pattern elements and styles on the outer packaging of products to attract consumer attention. However, traditional pattern packaging design has shortcomings, such as the inability to meet the personalized needs of different users in packaging design, and the lack of innovation in pattern elements in traditional design, which cannot convey the connotation that the product needs to express [3]. Therefore, a packaging beautification design method based on the combination of visual images and personalized patterns is proposed. Images are processed through pattern feature extraction technology to achieve personalized matching of pattern elements and styles. The innovation of the research lies in the emphasis on considering the impact of different pattern elements on packaging design, proposing a multi-model fusion pattern feature extraction technology to effectively extract pattern features and preserve details. Secondly, an improved transfer model is introduced for pattern matching training, achieving optimization of pattern packaging design. This technology has important application value in the field of packaging. While meeting the requirements of packaging beautification design, it improves the detail retention ability of traditional transfer models. Research technology will drive the development of the e-commerce industry and provide new methods and ideas for the beautification design of product packaging.

The research content is composed of six sections. Section I and Section II introduces the application of relevant visual images and the latest cutting-edge technologies, and discusses and analyzes the application of visual image technology in fields such as image segmentation and image matching. Section III analyzes the characteristics of packaging design and proposes a feature extraction model and pattern matching model to achieve personalized design of packaging. Section IV is to apply the mentioned technology to specific scenarios and assess the performance of the proposed packaging beautification design technology in practical scenarios. Section V delves in to discussion and finally, Section VI concludes the paper.

II. Related Works

Computer vision image is a technique that utilizes computers to process, analyze, and understand images. It is widely applied in fields such as facial recognition, image processing, and object recognition, and researchers all over the world have organized relevant research on this. The study by Penumuru et al. aimed to propose a universal method for automatic material recognition using machine vision and machine learning techniques to enhance the cognitive abilities of material processing equipment such as robots deployed in machine tools and Industry 4.0. The study selected four common materials and prepared and processed their surface datasets. By extracting the red, green, and blue components of the three primary color model as features and applying support vector machines and other classification algorithms, the proposed method has been studied and verified to recognize different material groups [4]. The results indicated that the proposed method could be implemented in a manufacturing environment without significant modifications. Secondly, the research of Uthayakumar et al. focused on computer vision-based applications in wireless sensor networks. Research results showed that visual sensors generated a large amount of multimedia data in sensors, while image transmission consumes more computing resources. To address this issue, a study proposed an image compression model using neighborhood related sequences. This algorithm performed bit reduction operations and further compressed the image through a codec. The proposed NCS algorithm improved the compression performance of sensor nodes and reduced energy utilization while maintaining high fidelity. Through experimental evaluation on test images, the results showed a better compromise between compression efficiency and reconstructed image quality [5]. Finally, Huang et al.'s research aimed to raise the real-time performance of image segmentation. The study introduced a fruit fly model into image segmentation and obtained a fusion image processing technique. By using optimization strategies to search for the optimal segmentation threshold, the model could converge faster and consume less time without sacrificing segmentation accuracy. The research results indicated that this method significantly reduced segmentation time while keeping the segmentation effect basically unchanged [6].

With the development of visual image technology, it has important applications in fields such as image design, segmentation, and matching. Agarwal et al. found that with the development of image editing tools, image forgery activities are on the rise. To protect the authenticity of images, a deep learning-based detection, replication, movement, and forgery image technology was proposed. This technology involved processes such as segmentation, feature extraction, dense depth reconstruction, and ultimately identifying tampered areas. Finally, the technology was applied to specific scenarios, and it had good image visual processing effects [7]. Li et al. found that effective image segmentation in image design faced challenges, and proposed a convolutional neural network that combines attention mechanism (AM). The network structure studied consists of a basic feature layer and an attention module, which is utilized to capture global information and enhance features. The experimental outcomes showed that this method was superior to other existing mainstream image processing methods and had fewer parameters, improving the application of visual technology in related fields [8]. Chen et al.'s research focused on the importance of image matching in fields such as augmented reality, synchronous localization, and visual design. The study improved the accuracy of feature matching in visual design by incorporating instance aware semantic segmentation into visual feature matching for corner detection and rotation. Research used pixel level object segmentation and semantic information limitation to perform feature matching on adjacent images. The research findings indicated that this method improved the accuracy of feature matching and met the requirements of visual design [9]. Hu et al.'s research was dedicated to the study of image segmentation techniques. So, a parallel deep learning algorithm with mixed AM was proposed to enhance the effectiveness of pattern design work. This algorithm extracted pattern feature information from preprocessed images and inputs the images into a mixed AM and densely connected convolutional network module. The mixed AM consists of spatial AM and channel AM. The experiment outcomes denoted that this technology can significantly improve the image processing efficiency of design work, while also improving the processing effect of image data [10].

In summary, computer vision image technology has important applications in many fields. With the advanced visual image and machine learning techniques, problems such as image editing, segmentation, and matching in image design can be effectively solved. However, there are relatively few applications of visual image technology in the field of product appearance. In this regard, applying visual image technology to the packaging beautification design process provides relevant technical guidance for product packaging design and beautification.

III. Construction of Packaging Beautification Model based on Personalized Pattern Matching

This section mainly focuses on the research of product packaging beautification design, proposing pattern feature extraction models and pattern personalized matching models for product packaging design, and constructing relevant models separately.

A. *Extraction of Personalized Packaging Pattern Features*

In recent years, with the continuous improvement of people's quality of life and consumption ability, pursuing personalized consumption has become a social development trend. Personalized product packaging design can not only impress people, but also enhance the competitiveness of the product with personalized patterns. Therefore, in response to the growing demand for personalized packaging appearance, a personalized packaging pattern matching technology based on visual image technology is proposed [11]. To meet user needs, it is necessary to fully consider pattern design elements. Taking blue and white porcelain products as a case study, in the design of packaging patterns for blue and white porcelain, it is necessary to extract target features based on consumer needs and product attributes [12]. The process of product feature extraction technology is shown in Fig. 1.

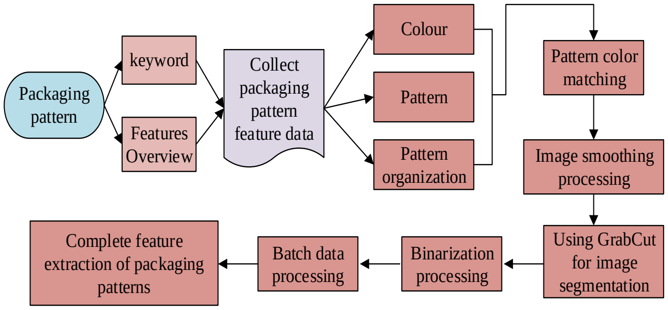

Packaging pattern
keyword
Features Overview
Collect packaging pattern feature data
Colour
Pattern
Pattern organization
Pattern color matching
Image smoothing processing
Using GrabCut for image segmentation
Binarization processing
Batch data processing
Complete feature extraction of packaging patterns

Fig. 1. Product feature extraction process.

According to the technical process in Fig. 1, feature extraction of patterns includes pattern, color, and tissue extraction. In the extraction of the above feature information, to meet the personalized design requirements of product packaging, it is necessary to process the above features accordingly. If the extracted pattern features contain a large number of organizational textures, it will have an impact on the personalized information processing of the pattern itself. Therefore, in the study, a Relative Total Variation (RTV) model is adopted to optimize the feature extraction. The RTV model can make the image texture smooth and highlight the main feature details needed [13]. In smoothing processing, any point in the product feature image is defined as p, and the RTV of the image's P points is calculated as shown in Eq. (1).

$$RTV(P)=\sum_{q\in N_P} w_{pq}\cdot\| I_P-I_{q_s}\|^2\cdot\lambda_r \tag{1}$$

In Eq. (1), N_P is the set of points adjacent to P. λ_r represents the degree of smoothness. w_{pq} is the weight between point P and adjacent point q_s. I_P and I_q are the grayscale values of point P and adjacent point q. After completing the image smoothing process, it is also necessary to segment the image in order to better obtain different background features [14]. In the study, GrabCut was used as an image segmentation technique to perform local segmentation on the target image. The specific process is shown in Fig. 2.

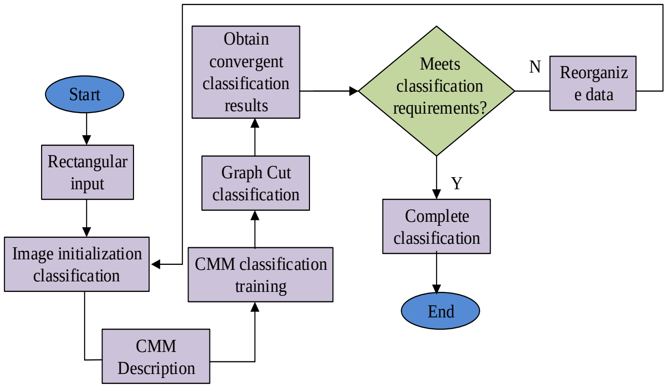

Start
Rectangular input
Image initialization classification
CMM Description
CMM classification training
Graph Cut classification
Obtain convergent classification results
Meets classification requirements?
N
Reorganiz e data
Y
Complete classification
End

Fig. 2. GrabCut segmentation process.

In the target feature map, multiple targets containing T rectangles are defined, and the external background of the rectangle is set to T_B, while the internal area of the rectangle is used as the foreground area, which is T_F. This expression is shown in Eq. (2).

$$\begin{cases} T_F=\varnothing \\ T_U=T_B \end{cases} \tag{2}$$

In Eq. (2), $\varnothing$ represents an empty bag. If any pixel T_F within T_B is initialized with a label, then the label $a_n=0$ represents the background pixel, and for each pixel in T_F, the T_F label is initialized with $a_n=1$ as the possible target pixel. The foreground and background regions are clustered into K-type using a clustering model, and a Gaussian Mixture Model (GMM) is constructed for the foreground and background. The three primary colors of the target pixel n are brought into each Gaussian component of the GMM model, and the K_n th Gaussian component of pixel T_F is the target pixel, as shown in Eq. (3).

$$k_n := arg\min_{KN} D_{\mathrm{n}}(\alpha_n,k_n,\theta,z_n) \tag{3}$$

In Eq. (3), θ represents the initial parameters of GMM, and z_n is the image matrix. For the given image data Z. D_n represents the Gaussian component. The GMM model is applied for parameter training, and the expression is shown in Eq. (4).

$$\theta' := arg\min_{\theta'} U(\alpha_n,k_n,\theta,z_n) \tag{4}$$

In Eq. (4), $U(\cdot)$ represents GMM parameter learning. The maximum minimum flow strategy is used to segment pixels and obtain the minimum energy, as shown in Eq. (5).

$$\min_{\{a_n,n\in T_U\}} = arg\min_{K} E(\alpha_n,k_n,\theta,z_n) \tag{5}$$

In Eq. (5), E represents the energy value. Repeating Eq. (3) and Eq. (5) until convergence is achieved to obtain the image segmentation result. Considering the issue of color difference in feature extraction, the Otsu segmentation method (OTSU) is adopted to handle the differences between extracted features. The OTSU idea is to segment a single feature, divide the target feature into foreground and background parts through grayscale features, and achieve black and white color gamut division by searching for grayscale levels and OTSU thresholds [15]. OTSU image segmentation is shown in Fig. 3.

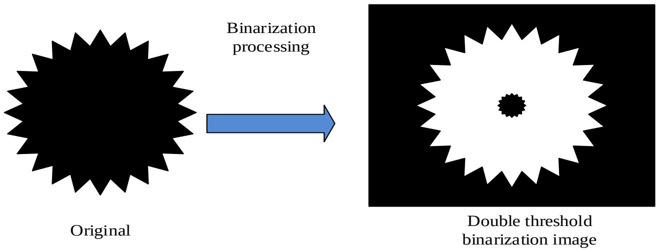


Fig. 3. Schematic diagram of OTSU image segmentation.

It defines the grayscale image as F, uses F as a matrix of $M\times N$, sets the pixel value to (0255), and uses n_i as the amount of pixels with a grayscale pixel level of i. The probability of selecting the grayscale pixel i is denoted in Eq. (6).

$$\begin{cases} p_i=\dfrac{n_i}{n_0+n_1+\cdots+n_{255}} \\ \sum_{i=0}^{255} p_i=1 \end{cases} \tag{6}$$

In image segmentation, the foreground and background segmentation thresholds of the image are set to k_l. According to the segmentation threshold, there are a large number of pixels that are greater than or less than k_l, namely C_A and C_B. The probability of selecting the two types of pixels is set to P_A and P_B, and the grayscale mean of the two types of pixels is set to m_A and m_B. If the grayscale level accumulation value is set to m_l, the global mean of the image is shown in Eq. (7).

$$m_G = p_A(k_l) \times m_A(k_l) + p_B(k_l) \times m_B(k_l) \tag{7}$$

In Eq. (7), there is a relationship as shown in Eq. (8).

$$p_A(k) + p_B(k) = 1 \tag{8}$$

Then, the expression equation of variance is used to obtain the value of the image segmentation method, as shown in Eq. (9).

$$\sigma^2 = p_A(k_l)(m_A(k_l) - m_G)^2 + p_B(k_l)(m_B(k_l) - m_G)^2 \tag{9}$$

In Eq. (10), σ is the spatial scale adoption number, and the square difference is subjected to deformation processing. The result is shown in Eq. (10).

$$\sigma^2 = \frac{(m_G * p_A(k_l) - m_l)^2}{p_A(k_l)(1 - p_A(k_l))} \tag{10}$$

The traversal is used to obtain the maximum threshold k_l between variances, and then re-segment the image through binarization. The result is shown in Eq. (11).

$$img(i,j) = \begin{cases} maxval & ifimg(i,j) > threshold \\ 0 & othenuise \end{cases} \tag{11}$$

The extraction of pattern features is the key to packaging beautification design, and it is necessary to extract the main pattern feature elements from the target, including patterns, colors, and organization, to provide basic elements for subsequent packaging beautification design.

B. Construction of a Personalized Pattern Transfer Model Based on Packaging Beautification

In product packaging beautification design, it is necessary to combine the extracted multiple style features with the target product, meeting both the product style features and the visual aesthetic design requirements. To effectively match the elements in the pattern with the target product, a personalized pattern transfer model based on the Improved Style Transfer Generative Adversarial Networks for Image to Illustration Translation (GANILLA) was proposed in the study. By fusing the features of different styles of patterns with the target, personalized packaging matching was achieved [16]. The GANILLA model was proposed by Samet Hicsonmez et al. in 2020 as an image style transfer learning model. In image feature processing, the original image content details were preserved as much as possible to achieve different style feature transfer methods. Among them, the structural framework of the GANILLA model is shown in Fig. 4.

From Fig. 4, the GANILLA model used convolutional layers for downsampling. At the same time, the inverse convolutional layer was used for upsampling, and a concatenated residual layer was used in the model. The inverse convolutional layer was replaced by a sampling operator. In the given pattern element features, it was necessary to combine the extracted pattern elements with different styles to fuse and generate new design patterns [17]. The pattern features are independent data, and the product packaging data is target data. The GANILLA model sampled feature maps through a skip connection generator. At the same time, to better preserve the transmission pattern features, upsampling and skip connections were used to merge high-level and low-level features, thereby improving the image composition quality [18]. The distance between the synthesized image and the real image is defined as $L1$, where the number of samples is set to N, the predicted pixels are set to y, and the pixels of the real image are x. The comparison between the synthesized image and the real image is shown in Eq. (12).

$$L_{rec} = \frac{1}{N}\sum_{i}^{N}\frac{\|y - x\|}{WHC} \tag{12}$$

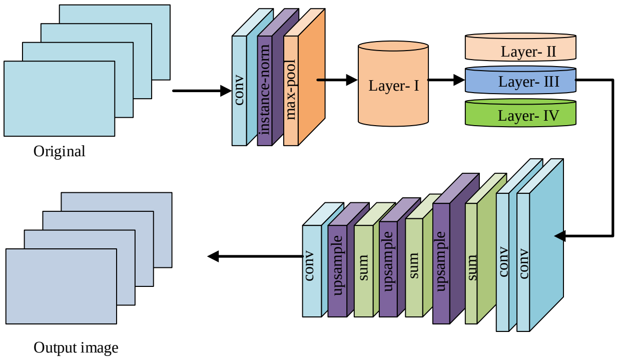


Fig. 4. GANILLA model structure.

In Eq. (12), W, H, and C respectively represent the width, height, and amount of channels of the image. Then, the discriminator adversarial loss is calculated, as shown in Eq. (13).

$$\begin{aligned} L_{GAN}(G,D) &= E\left[\log(Dx)\right] \\ &+ E\left[\log(1 - D(G(x')))\right] \end{aligned} \tag{13}$$

In Eq. (13), x' means the input damaged image, G represents the output target, D is the discriminator, and E represents the energy loss value. Then the joint loss is calculated, as shown in Eq. (14).

$$L = \lambda_1 L_{rec} + \lambda_2 L1 \tag{14}$$

In Eq. (14), λ_1 and λ_2 are both loss optimization parameters. In the actual pattern transfer, although the GANILLA model has good adaptability to the processing of pattern texture features, there are still shortcomings in handling individual feature details, such as the problem of detail loss in the transformation of texture features. In this regard, improvements will be made from two methods: feature analysis and model performance. In the analysis of pattern features, attention SE block modules will be added to the Residual Block layer to improve the model's attention to key positions in the image. At the same time, the addition of AMs can improve the acquisition of useful features without suppressing useless features [19]. The SE block module structure framework is shown in Fig. 5.

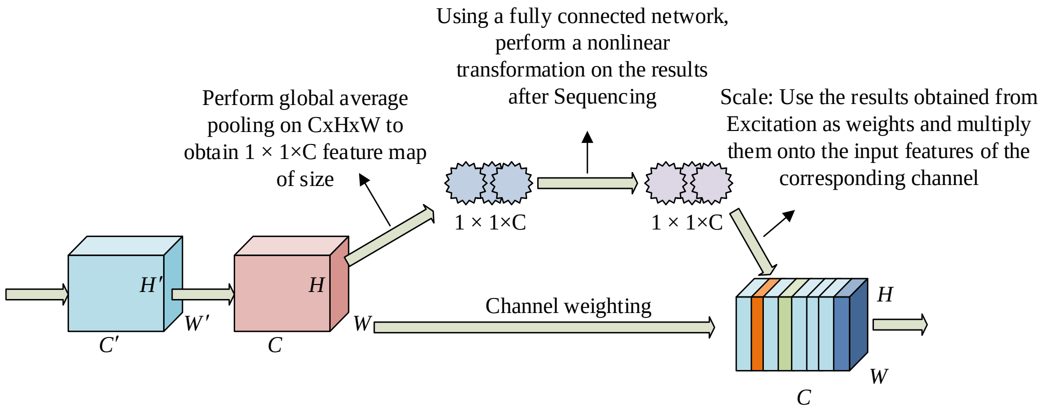

Using a fully connected network, perform a nonlinear transformation on the results after Sequencing
Perform global average pooling on CxHxW to obtain 1 × 1×C feature map of size
Scale: Use the results obtained from Excitation as weights and multiply them onto the input features of the corresponding channel
1 × 1×C
1 × 1×C
H′
W′
C′
H
W
C
Channel weighting
H
W
C

Fig. 5. SE block module structure framework.

In terms of model performance, considering the addition of AM, the computational complexity of model parameters is increased, and a parameter compression model, Residual block, is introduced to reduce network parameters and floating-point computational complexity in the model. Two generators and discriminators are included in the generative adversarial loss function of the improved GANILLA model. Firstly, the adversarial loss is adopted in the mapping network, and the target mapping relationship is expressed as Eq. (15).

$$G^*, F^* = arg\min_{G,F} \min_{D_X, D_Y} L(G, F, D_X, D_Y) \tag{15}$$

In Eq. (15), F represents the mapping target, and F and D_Y are the discriminators corresponding to the X domain and Y. The image $G(X)$ generated by G will continuously approach Y, enhancing the similarity between the two sides of the mapping. D_Y can be used to distinguish the two targets y and $G(X)$. Simultaneously, the minimum target in the target G mapping relationship is applied to counter the discriminator. In adversarial training, learning training can be used to learn the mapping relationship between G and D [20]. Finally, the various loss functions are combined, and the loss optimization parameter λ is introduced to optimize the real image pixel x. The target loss is shown in Eq. (16).

$$\begin{aligned} L(G, F, D_x, D_\gamma) &= L_{GAN}(G, D_Y, X, Y) \\ &+ L_{GAN}(F, D_X, X, Y) + \lambda L_{cyc}(G, F) \end{aligned} \tag{16}$$

In Eq. (16), the larger the loss optimization parameter value λ, the closer each pair of discriminators will be. Through the above techniques, the extracted personalized pattern elements can be style transferred to achieve personalized design of packaging patterns.

IV. Algorithm Model Simulation Testing

This section conducted performance tests on the two proposed models to evaluate their practical application effects. The main evaluation indicators included pixel accuracy (PA), signal-to-noise ratio (SNR), peak signal-to-noise ratio (PSNR), and loss.

A. Experimental Analysis of Pattern Feature Extraction

To improve the proposed packaging beautification design model, experimental testing was conducted on the Windows 10 64 bit platform. The processor was a Zhiqiang 64 core processor, the graphics card was NVIDIA RTX4060ti, and the running content was 64G. The experimental data was sourced from the integrated packaging graphic design website, which included 15564 image feature data, including pattern, color, tissue and other feature data. The initialization parameters of the experimental model are expressed in Table I.

TABLE I. Model Initial Parameters

Parameter indicator type	Numerical value
Smoothness parameter r λ_r	0.005 to 0.03
Spatial scale parameter σ	0 to 6
Model iteration times	100
Float	Le-3
Execute initialization times	1

PA and SNR were introduced as evaluation indicators. 12 patterns were selected for feature extraction, and some pattern samples are shown in Fig. 6.

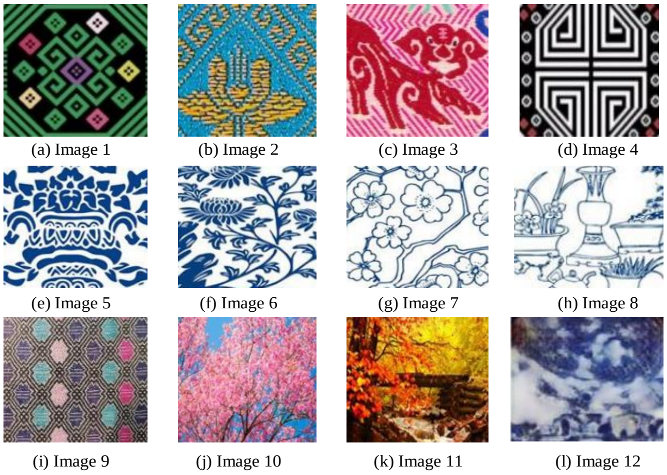

(a) Image 1 (b) Image 2 (c) Image 3 (d) Image 4
(e) Image 5 (f) Image 6 (g) Image 7 (h) Image 8
(i) Image 9 (j) Image 10 (k) Image 11 (l) Image 12

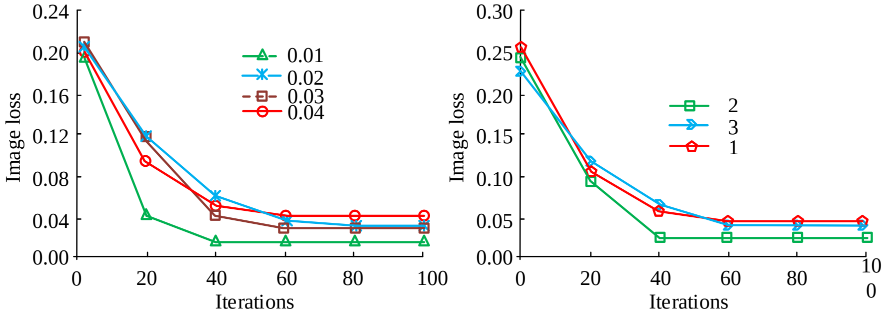
Fig. 6. Partial pattern data.

In actual feature extraction, the difference between λ_r

value and σ would directly affect the effect of image detail texture processing. Therefore, it is necessary to compare the image feature extraction under different parameters, as shown in Fig. 7.

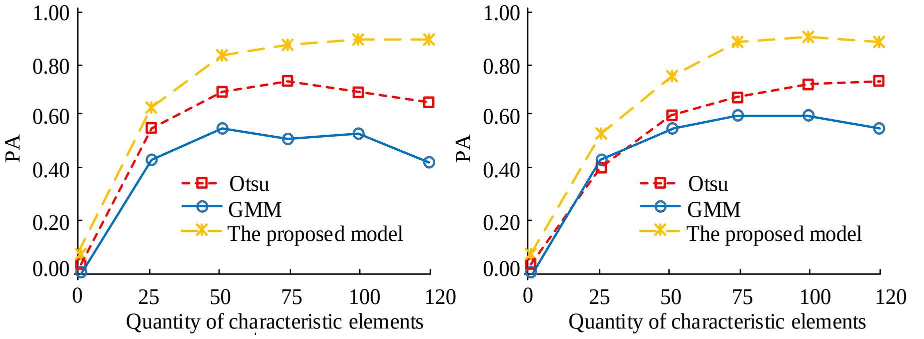
Fig. 7(a) and Fig. 7(b) express the comparison outcomes of λ_r and σ, respectively. Among them, when the λ_r parameter was set to 0.01, the model training image loss was the lowest, which was 0.012. At the same time, comparing the σ parameter settings of the model, when σ was set to 2, the training loss of the model was the lowest and the convergence effect could be achieved the fastest. Therefore, in subsequent experimental testing, the parameters were set to 0.01 and the σ parameter was set to 2. Image 1 and Image 2 were selected for feature extraction testing, and the test results are shown in Fig. 8.

Fig. 8(a) denotes the feature extraction test outcomes of Image 1. According to the results, when the amount of image elements was 120, the PA was the highest, at 0.903. Compared to this, both OTSU and GMM had a decrease in feature extraction performance after the number of pattern elements was 75. When the amount of image elements was 120, the PA of OTSU and GMM was 0.689 and 0.403, respectively. Fig. 8(b) shows the feature extraction test results of Image 1. The proposed model realized the highest PA of 0.909 when the number of pattern elements was 120, while the GMM model gradually decreased in PA after the amount of pattern elements was 100. The highest PA of OTSU and GMM were 0.786 and 0.526, respectively. Finally, the SNR was used to reflect the quality of feature extraction for different model elements. The effect of extracting cluster features for multiple models is shown in Fig. 9.



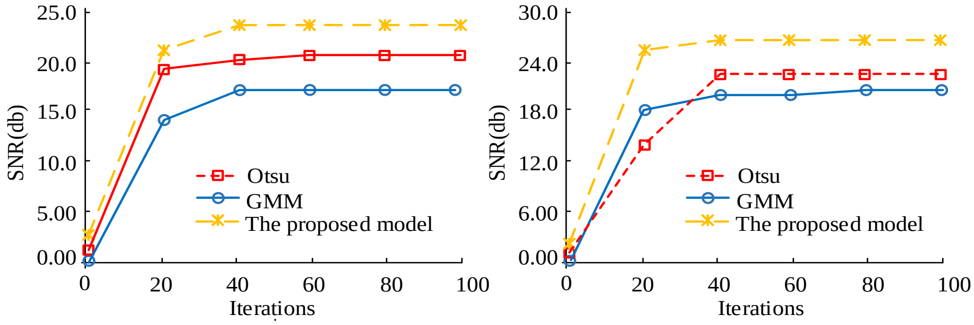
(a) Comparison of values for λ_r (b) Comparison of values for σ

Fig. 7. Comparison of image loss under different parameters.



(a) Image 1 (b) Image 2

Fig. 8. Comparison of pixel accuracy among different models.



(a) Image 1 (b) Image 2

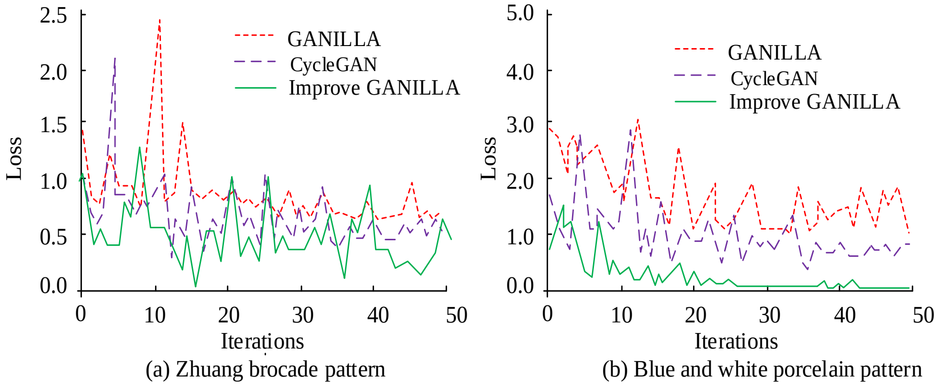
Fig. 9. Comparison of optimal SNR among different models.

Fig. 9(a) shows the feature extraction quality results of Image 1. From the data outcomes, as the amount of iterations increased, the image quality of all three models continued to improve. The best performing model was the one proposed, with an optimal SNR of 23.56 at convergence, followed by OTSU with an optimal SNR of 20.65, and GMM with an optimal SNR of 17.56. Fig. 9(b) shows the feature extraction quality results of Image 2. Before 40 iterations, the GMM model performed better than the OTSU model in extracting pattern features. In the early training, the GMM model had better feature extraction performance than the OTSU model. After training, the OTSU model could retain more black and white details during training, which was better than the GMM model. Overall comparison showed that the proposed model had the best feature extraction performance, followed by OTSU, and finally the GMM model. The optimal SNRs for the three models, from high to low, were 25.65, 22.86, and 19.98, respectively.

B. *Experimental Analysis of Personalized Packaging Pattern Matching*

In the personalized packaging matching experiment section, the selected pattern features would be used as experimental data, and the proposed improved GANILLA model would be used as the pattern matching model. Meanwhile, the Cycle-Consistent Generative Adversarial Networks (CycleGAN) and GANILLA were introduced as experimental testing benchmarks. In the parameter settings, the Bachsize was 1, the optimization algorithm was Adam, the initialization step factor was 0.0002, and the experimental analysis was completed using the Pytorch platform. Mapping loss (Loss) and PSNR were introduced to reflect the quality of reconstructed images in the model. Two types of styles, Zhuang brocade pattern and blue and white porcelain pattern were selected for packaging matching. Fig. 10 shows the Loss results of different models.

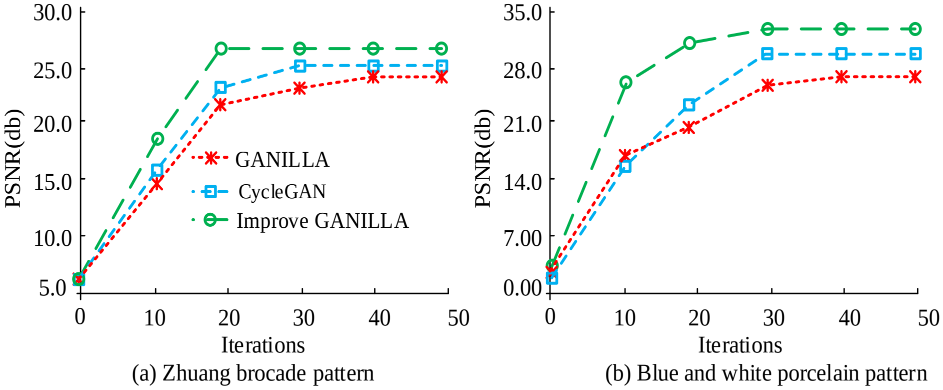
Fig. 10(a) shows the packaging matching test results under the Zhuang brocade pattern. In the early stage of testing, both the CycleGAN model and the GANILLA model showed significant fluctuations. Considering the overall situation, it was possible that the two models were unable to accurately recognize the color of the pattern during the early training, resulting in a decrease in image transfer quality. Compared to this, the proposed model had smaller overall fluctuations during training and lower Losses. When GANILLA, CycleGAN, and improved GANILLA converged, the Losses were 0.542, 0.512, and 0.135, respectively. Fig. 10(b) shows the packaging matching test results under the blue and white porcelain pattern. Due to the presence of more feature elements in the blue and white porcelain pattern, it further tested the model's ability to recognize features. Overall, the proposed improved GANILLA model performed the best with a Loss of 0.236 at convergence, while the CycleGAN model and GANILLA model had Losses of 0.956 and 12.35 at convergence, respectively. Finally, the PSNR was used to reflect the quality effect of pattern matching, as shown in Fig. 11.



(a) Zhuang brocade pattern

(b) Blue and white porcelain pattern

Fig. 10. Comparison of mapping loss results for different models.

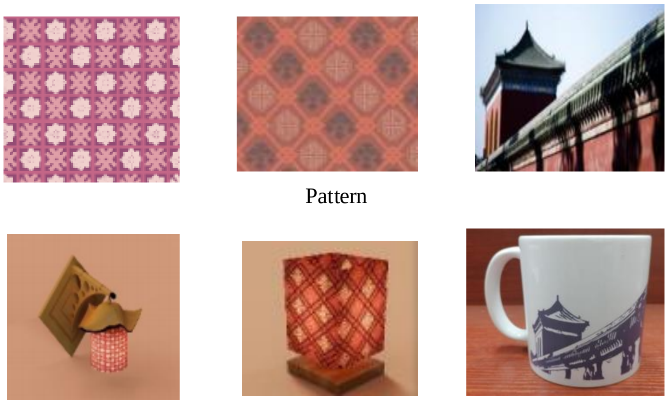


(a) Zhuang brocade pattern

(b) Blue and white porcelain pattern

Fig. 11. Comparison of peak signal-to-noise ratio for different model pattern combinations.

Fig. 11(a) and Fig. 11(b) respectively show the packaging matching test results of Zhuang brocade pattern and blue and white porcelain pattern. In the combination of Zhuang brocade patterns, the proposed improved GANILLA converged the fastest and had the highest PSNR of 25.65 among the three models. The GANILLA model performed the worst, with the best PSNR of 24.15 during convergence. In the combination of blue and white porcelain patterns, the best performance was still the proposed improved GANILLA model. The improved GANILLA, CycleGAN, and GANILLA had the best PSNRs at convergence of 32.32, 29.32, and 27.03, respectively. From the above experiment, the proposed model had better testing performance in packaging pattern matching. The matching effect of the final packaging pattern is shown in Fig. 12.



Pattern

Matching scheme

Fig. 12. Packaging pattern matching effect.

V. Discussion

In recent years, with the rapid development of the e-commerce industry, product packaging has played an increasingly important role in attracting consumer attention and increasing sales. The diversification and personalization of packaging design have become one of the important strategies for brand competition. The packaging beautification design based on the combination of visual images and personalized patterns is an innovative design method proposed to meet this demand. The study will conduct in-depth discussions on it. Visual image technology refers to an interdisciplinary technology that utilizes computer vision and image processing techniques to analyze, process, and apply images. It mainly includes image acquisition, processing, analysis, and application. In the field of design, visual image technology has been widely applied in product, web, advertising designs, and other aspects. By processing and analyzing images, functions such as image enhancement, restoration, segmentation, and detection can be achieved, thereby improving design effectiveness and user experience. Packaging beautification design refers to the design and adjustment of the appearance, pattern, color, form, and other aspects of product packaging to meet the aesthetic needs and brand image of consumers, and to attract the attention of target consumers, enhancing the market competitiveness of the product. Packaging beautification design includes various contents, such as the selection and design of packaging patterns, color matching, material selection, position and size of patterns, etc. By cleverly utilizing these design elements, product packaging can be made more attractive, unique, and effectively convey the brand's value and characteristics.

A visual image-based packaging beautification design technology was proposed in the study, which utilized advanced image segmentation processing technology and image transfer technology to achieve personalized and efficient development of packaging images. In the experiment of pattern feature extraction, by comparing the image feature extraction under different parameters, it was found that the proposed model achieved the best training loss and convergence effect when the parameters were set to 0.01 and 2. Meanwhile, compared with traditional OTSU and GMM models, the proposed model performed better in PA and SNR, and had higher feature extraction quality. This indicated that visual image technology had significant advantages in packaging image data processing compared to similar technologies, laying the foundation for subsequent packaging beautification design. In the personalized packaging pattern matching experiment, by comparing the proposed improved GANILLA model with CycleGAN and GANILLA models, it was found that the improved GANILLA model achieved better Loss and PSNR ratio results in the packaging matching of Zhuang brocade patterns and blue and white porcelain patterns. This meant that the proposed model could more accurately transfer the colors and features of patterns during the pattern matching process, improving the quality and effect of pattern matching.

It can be seen that by using visual image technology, accurate extraction and analysis of image features can be achieved, providing scientific basis and guidance for packaging beautification design. The proposed technology also has significant advantages compared to similar technologies. In the experiments of pattern feature extraction and pattern matching, the proposed techniques have shown excellent results. Therefore, research-proposed technology can make packaging design more creative and personalized, improving the attractiveness and competitiveness of packaging.

VI. Conclusion

Product packaging design is one of the important means to showcase product functions and concepts, and the effectiveness of product packaging design has a significant impact on product competitiveness. Traditional packaging design faces problems such as long design cycles and single packaging design. An intelligent packaging pattern beautification technology was proposed for this. Firstly, based on product positioning, a pattern feature extraction method was proposed, which preserved the main features of pattern elements through pattern smoothing, segmentation, and binarization processing. Secondly, a pattern matching technique was proposed, which used the GANILLA model to train features and experiment with the transfer of pattern features. Simultaneously, AM was introduced to improve the model and enhance image details. In the feature extraction experiment of Image 1, when the number of image elements was 120, the PA of OTSU, GMM, and the proposed model were 0.689, 0.403, and 0.903, respectively. In the SNR test, the optimal SNRs of the proposed model, OTSU, and GMM models in Image 2 were 25.65, 22.86, and 19.98, respectively.

In the packaging pattern matching experiment, the Losses of different models were compared. Under the Zhuang brocade pattern, the sound losses of CycleGAN, GANILLA, and improved GANILLA were 0.542, 0.512, and 0.135, respectively. Finally, the matching effects of different model patterns were compared. In the PSNR test of blue and white porcelain patterns, the improved GANILLA, CycleGAN, and GANILLA had the best PSNRs at convergence of 32.32, 29.32, and 27.03, respectively. The proposed model had excellent application effects in packaging beautification design. However, the study did not provide personalized design for different target groups. However, there are also limitations to the research technology. This technology has a slower efficiency in image processing, and in the future, model parameters can be optimized to improve image processing efficiency. At the same time, image data can be preprocessed to improve the application effect of the technology.

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Blockchain-based Cannabis Traceability in Supply Chain Management

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***Abstract*—The typical cannabis supply chain is encountering obstacles with the traceability of product regulations and standards. It is a complex structure involving multiple organizations and healthcare products. Questionable products finding their way onto the legal market are potentially dangerous. The proportion of Tetrahydrocannabinol (THC)/Cannabidiol (CBD) and the source of the cannabis strains have an impact on human treatment, limiting the traditional cannabis supply chain from seed to sale. Currently, the cannabis supply chain involves multiple stakeholders, which complicates the validation of various essential criteria, including license management, Certificate of Analysis (COA), and conformance quality standards and regulations. Existing traceability systems involve a centralized authority, leading to a lack of transparency and tracking system immutability. This study offers a Polygon blockchain-based strategy using smart contracts and decentralized on-chain and off-chain storage for efficient information searches in the cannabis supply chain. Eliminating the need for middlemen, the blockchain-based solution gives data security and transaction immutability history to all stakeholders. The storage structure comprises on-chain and off-chain components, algorithms, and the operating principles of the suggested solution. In addition, the suggested system delivers query efficiency and assures supply chain management authenticity and dependability. To assess the performance of the cannabis supply chain, scalability in developing a blockchain-based traceability process avoids delays and high transaction fees.**

***Keywords*—Blockchain; cannabis; traceability; supply chain management; polygon; on-chain and off-chain**

I. Introduction

The cannabis supply chain comprises a complicated network of enterprises. In conjunction with healthcare goods, the bad impacts are detrimental to individual health, the economy, and society. The supply chain for cannabis extract products consists of the selection of seeds, cultivation, production, distribution, and sale of the finished product. Therefore, traceability of product standards and regulations is prone to a lack of confidence, transparency, and immutability of the tracking system. Due to the COVID-19 pandemic, the challenge is to prevent questionable products from finding their way onto the legal market. Consequently, providing traceability is essential for isolating and eliminating potentially dangerous products. Cannabis-extracted products are produced from an identifiable source to make them appear genuine, such as apoptosis induction on human cancer cells by cannabis sativa L [1]. The proportion of THC/CBD is also used as a criterion for identifying cannabis strains or cultivars [2].

As reported by the World Health Organization (WHO), cancer is a primary contributor to mortality worldwide, responsible for more than 10 million deaths in the year 2020. It is estimated that by 2041, there will be more than 30 million new cases and more than 20 million deaths. Treatment with the use of chemotherapy is a popular choice due to its high efficiency. However, it has been found that many patients experience side effects from the use of the drug, including the high cost of medicines or treatment methods [3]. Currently, the US Food and Drug Administration (US FDA) approves the utilization of Dronabinol and Nabilone, which contain THC as the main ingredient, for treating cancer patients experiencing dizziness, nausea, vomiting, and loss of appetite due to chemotherapy [4].

In 2021, the legal cannabis industry provided US$ 17.8 billion to the world economy. This figure is expected to increase by 25.3% between 2022 and 2030 [5]. Thailand is at the leading edge of cannabis liberalization in Southeast Asia. The region decriminalized medical cannabis in 2018, and Thailand then decriminalized the cannabis plant in a push toward commercialization in June 2022 [6].

Fig. 1 depicts the cannabis supply chain distribution process. A seed provider is responsible for distributing seeds to Thailand’s FDA-approved producers (Thai FDA). The grower is responsible for nurturing cannabis plants from seed and must register a “Plookganja” application. The grower then delivers the cannabis plants to the manufacturer. The manufacturer produces cannabis extract products in lots and sends each lot to a laboratory. The two most prevalent cannabinoids produced from cannabis are CBD and THC.

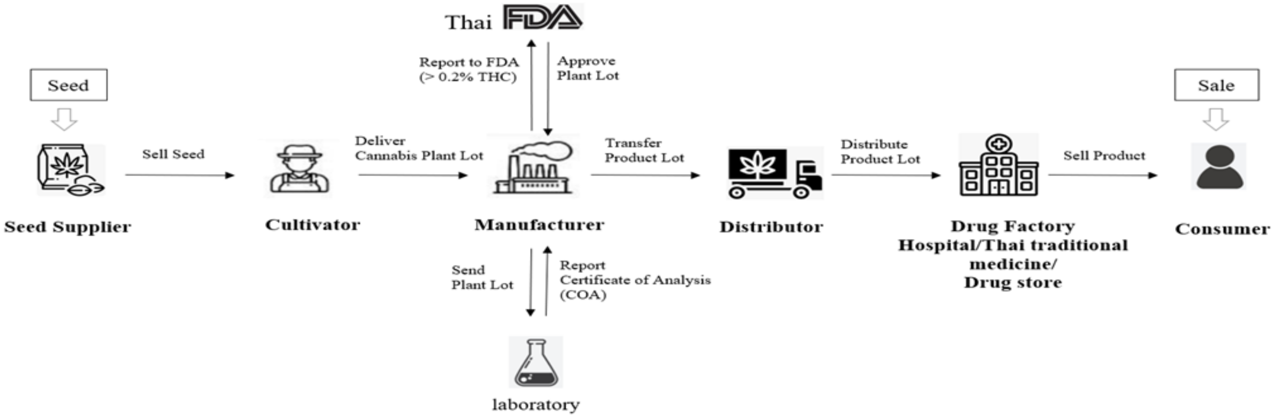

Fig. 1. Product flow and stakeholder relationship in the cannabis supply chain from seed to sale.

In the case of THC, the concentration level exceeds 0.2% and must be tested with the results reported to the Thai FDA. The distributor receives a large amount of cannabis extract products and is responsible for transferring them to hospitals, medicine practices, and drug stores. Finally, they dispense the products to consumers typically based on formulated, processed, or synthetic cannabis sold as a finished product. From seed to sale, the whole cannabis supply chain can be traced and validated. This can help reduce the risk of errors, fraud, or other irregularities that may occur in the supply chain. This includes tracking the origin of the cannabis plant, processing the plant, and distribution of the final product. Consequently, monitoring, improving quality control, and tracking product standards and regulations are fundamental to cannabis supply chain traceability.

Several nations, including the United States [7, 8], Canada [9], the Asia-Pacific region [10], and so on, are progressively emphasizing and mandating the necessity of cannabis traceability. Thai cannabis products are subject to strict regulations, and the IT system and applications can help ensure they are not tampered with or diverted from the legal supply chain. Decentralized control makes it difficult for bad actors to alter or manipulate the data recorded on the ledger.

Blockchain represents a distributed and decentralized ledger that retains and distributes all transactional records or alternate data and enables all forms of peer-to-peer value transactions [11], protected by encryption and regulated through a process of collective agreement [12]. The data structure of the blockchain is composed of a succession of blocks. A network of computers maintained by users or participants through a network of computers constitutes the interconnected sequence of a distributed ledger or list of entries. Cryptography is employed by blockchain to handle and authenticate ledger transactions. Users of the network authorize and record all transactions. Apart from being assigned to chronological timestamps, being interconnected with the previous block, and becoming unalterable once uploaded onto the network, these blocks constitute an essential building block of the blockchain structure [13]. Continuous updates of real-time data reduce the necessity for intricate and error-prone reconciliation processes involving the internal records of each party.

Blockchain is an essential technology for modernizing supply chain management in the industry 4.0 era [14], including the Internet of Things (IoT), and smart contracts [15]. Cannabis supply chains are concentrating on transparency, real-time monitoring, and securing transactions. Customers demand product visibility and traceability throughout the entire supply chain.

This paper seeks to illustrate how blockchain technology may be employed for the traceability of cannabis extract goods. By employing the distributed storage, hash encryption, and programmable smart contract attributes inherent in blockchain technology, this research proposes designing and implementing a blockchain-based traceability system for cannabis extract goods. The system design method is detailed in-depth, and the associated important breakthrough technologies, encompassing both the on-chain and off-chain storage architectures, are elucidated. To demonstrate the system's viability, the blockchain network is based on performance testing and actual applications of cannabis supply chain traceability.

The significance of this study is summarized as follows:

- A blockchain-based system that offers data security, immutability, and decentralized control for cannabis extract products is offered for the cannabis supply chain.
- A smart contract capable of processing multiple transactions between stakeholders in the cannabis supply chain is presented.
- A blockchain network founded on a Polygon and cannabis supply chain traceability is presented to facilitate the storage and retrieval of cannabis product traceability data.
- As the recommended solution, blockchain-based cannabis traceability is developed and evaluated for performance and cost.

The composition of the subsequent parts can be outlined as follows: In Section II, a literature review of blockchain-based traceability solutions is presented. Section III elaborates on the construction of a smart contract and the traceability of the cannabis supply chain. Section IV describes the implementation and test performance of the suggested system.

Section V provides an evaluation, and then Section VI describes the discussion. Finally, Section VII provides conclusions and recommendations for future research.

II. Related Work

This part provides a critical assessment of current initiatives to solve the product traceability problem. Relevant literature concerning traceability in supply chain management utilizing blockchain technology is recognized and assessed.

A. *Tradition Efforts for Supply Chain Traceability*

Traceability is characterized by the capacity to obtain any or all information pertaining to an item throughout its life cycle by identification methods. Traceability of the supply chain ensures that when quality-related issues arise, the raw materials or processing links in question can be swiftly verified, product recalls can be conducted as needed, and targeted penalties can be used to enhance the quality and safety of cannabis products.

Traceability is shown to be an effective strategy for regulating product quality across the local and global supply chain. Existing supply chain management systems have generally used barcodes and RFID tags for agricultural goods or pharmaceuticals. For example, Qian et al. [16] designed and implemented a system for milling wheat flour by combining 2D barcode and RFID technologies. Jabbar et al. [17] adopted GS1 standard barcodes with a serialized unique product identity, lot production number, and expiry date. The end consumer can utilize the QR code and/or RFID tag to enable them to read all the immutable traceability information [18, 19]. Other technologies have been developed to improve the traceability system [19], such as near-field communication (NFC), wireless sensor networks (WSN), cloud computing technology (CCT), and DNA barcoding. However, the typical traceability system does not sufficiently control the information's openness, making it susceptible to manipulation.

B. *Blockchain-based Solution for Cannabis Supply Chain Traceability*

Conventional approaches to traceability in the cannabis supply chain frequently adopt centralized systems, which tend to lack transparency at the participant level, allowing the central authority to manipulate data without notifying other involved parties.

Supply chain management in a range of sectors makes substantial use of blockchain technology to assist supply chain operations. Many sectors benefit from block-chain-based solutions, such as the agricultural food (agri-food) sector [20-29] to ensure data provenance, decentralized control and gives a secure, immutable history of trans-actions to all parties. In medicine supply chain, Musamih et al. [25] introduced the smart contract to verify data provenance, remove intermediaries, and provide all participants with a safe, unchangeable record of all transactions. Furthermore, the luxury goods supply chain, Chen et al. [30] introduced the smart contract to execute all information related to the production and logistics process of luxury product anti-counterfeiting. Kang et al. [31] introduced the enhancing traceability and authenticity in wine supply chain through a Stackelberg game-theoretical analysis.

Blockchain platforms have been developed to facilitate and accelerate the development of a decentralized application process in supply chain traceability projects. Two popular methods are Ethereum and Hyperledger Fabric.

Shahid et al. [22] and Babu et al. [32] suggested an Ethereum-based solution for the blockchain-based agri-food supply chain that uploads all blockchain-based transactions to IFS (IPFS). An efficient, safe, and reliable storage system creates a hash of the data stored on the blockchain. Using smart contracts and supporting algorithms, this technology displays system interactivity.

Yang et al. [20] introduced the use of Hyperledger Fabric in a blockchain-based traceability system designed for agricultural products such as fruits and vegetables. This system not only improves query efficiency and safeguards privacy but also ensures the legitimacy and dependability of data in supply chain management, all while aligning with the demands of practical, real-world applications.

Nevertheless, the usage of Ethereum with Hyperledger Fabric offers difficulties, including scalability and cost effectiveness.

III. Design for A Blockchain-based Cannabis Traceability System In Supply Chain Management

A. *System Framework*

This study assesses the traceability of cannabis products within Thailand's cannabis supply chain, spanning from the initial stages, such as cannabis seed selection, cultivation, and production, to the ultimate point of sale, where cannabis products are made available to consumers. The first layer of the cannabis supply chain involves selecting the seed of cannabis strains and the effect of seed storage methods on cannabinoids and psychoactive cannabinoids present in cannabis plants. In order to comply with regulations and record essential information about seeds, sales and purchases, and licensing, it is required to conduct an audit throughout the process of selecting seeds. Cannabis cultivation involves planting, transplanting, watering, harvesting, drying, and recording information on the transplant date, pollination control, fertilizer, harvesting process, drying weight, and other key elements. The extraction process requires the provision of the lot number, processing data, extracted oil weight, extraction gain/loss, and COA. Distribution requires a packing number for the lot, delivery information, and shipment date. Furthermore, the entire process is conducted under controlled environmental conditions at every stage, as factors such as temperature, humidity, or other elements can impact the content of CBD and THC. Starting at the distributor level, the retailer obtains limited quantities of finished products equipped with traceable identifiers, which are then sold to consumers. The application programming interface constitutes the second layer (API). The API interfaces directly or indirectly with a blockchain node or client network [33].The third layer, which comprises the traceability system, possesses the capability to identify, track, and trace individual cannabis product components as they navigate through the entire supply chain, spanning from the initial stage of seed selection to the end consumer. The traceability system's data collecting [34], data storage [35, 36], and data processing [37] comprise its data gathering layer. The aim of data collection is to identify and collect the data sources for all units of measurement.

Data storage is used to extract the data from multiple forms and sources into the data warehouse. Data processing analyzes and separates the on-chain and off-chain data. The blockchain is comprised of essential elements, including a smart contract, a consensus algorithm, a blockchain application, and digital storage. Digital data are stored in a decentralized architecture, allowing worldwide access to unused hard drive space. The decentralized infrastructure offers an alternative to centralized cloud storage [38] and is capable of alleviating a number of problems related to centralized systems. As seen in Fig. 2, An abstract model for managing cannabis traceability within the supply chain using blockchain technology [39] is predominantly constituted by four layers: the cannabis supply chain layer, the data interface layer, the traceability system layer, and the blockchain layer.

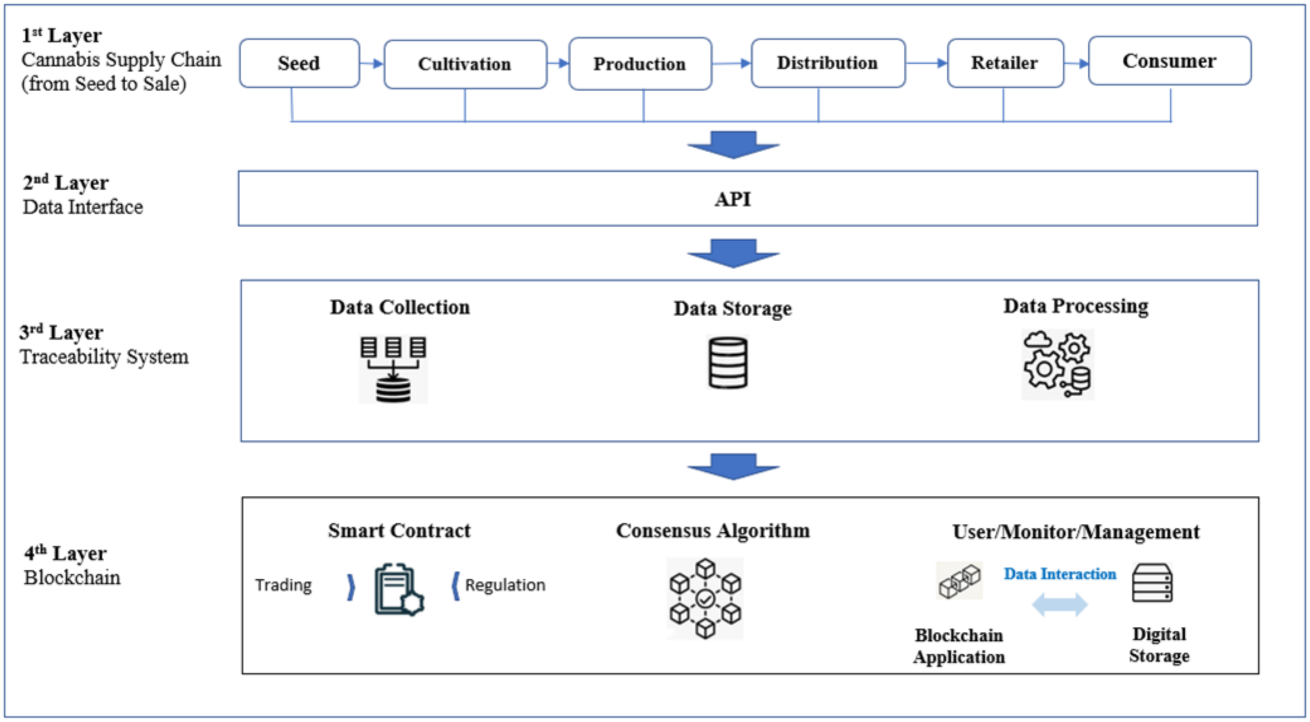

Fig. 2. An abstract model for managing cannabis traceability within the supply chain using blockchain technology.

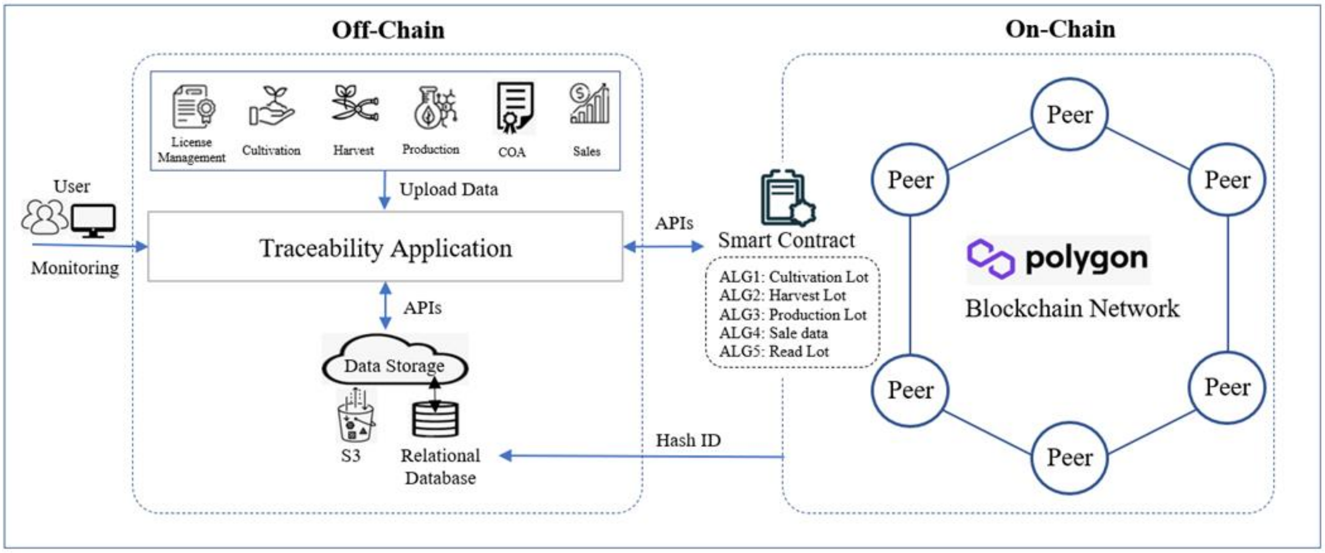

Fig. 3. Architecture of a blockchain-based cannabis traceability system.

B. On-Chain and Off-Chain

The current storage method of the blockchain traceability system requires the direct entry of traceability information for every node of cannabis items directly into the blockchain. As the number of nodes rises, so does the quantity of transaction data, increasing the storage stress on the blockchain. Given the chain-like configuration of the blockchain, query efficiency is relatively poor; only those of the same blockchain network can gain entry to the chain ledger's data. This research develops the storage mode of a blockchain-based traceability system for cannabis goods, which includes a distributed database of traceability information under an on-chain system. Once the traceability data is input into the system, it undergoes a categorization process. The public information about the product is preserved within the local database. As shown in Fig 3, the encrypted ciphertext is posted, and the hash ID of the public information is appended to the blockchain before being conveyed to the relational database.

Fig. 4 presents a data flow diagram illustrating the cultivation data, harvest data, production data, and distribution data between off-chain and on-chain. In traceability applications, all transactions, images, and data are uploaded by the participants. All participants are required to be licensed when uploading the information onto the database as shown in Table I.

TABLE I. VERIFICATION OF PARTICIPANT INFORMATION

Participant	Information	Verification
Seed Supplier	Seed supplier name, Registration, Address	Online
Cultivator	Cultivator name, License, Field name, GPS	Online
Harvest	Harvest name, License, Address, Dryer type	Online
Manufacturer	Manufacturer name, License, Address, Extractor type	Online
Distributor	Distributor name, Driver license, Transportation type	Online
Retailer	Retailer name, License, Address	Online
Lab	Lab name, License, Address	Online
FDA	Name, License, Address	Online

The lot number uploaded by the cultivator is automatically generated using the QR code to prevent error and fraud. The cameras are installed in the field for communicating and taking videos. Blockchain via smart contracts can be automatically programmed to impose penalties on the cultivator if they act dishonestly. Any peers or stakeholders in the blockchain can trust that their content can be disputed or refuted.

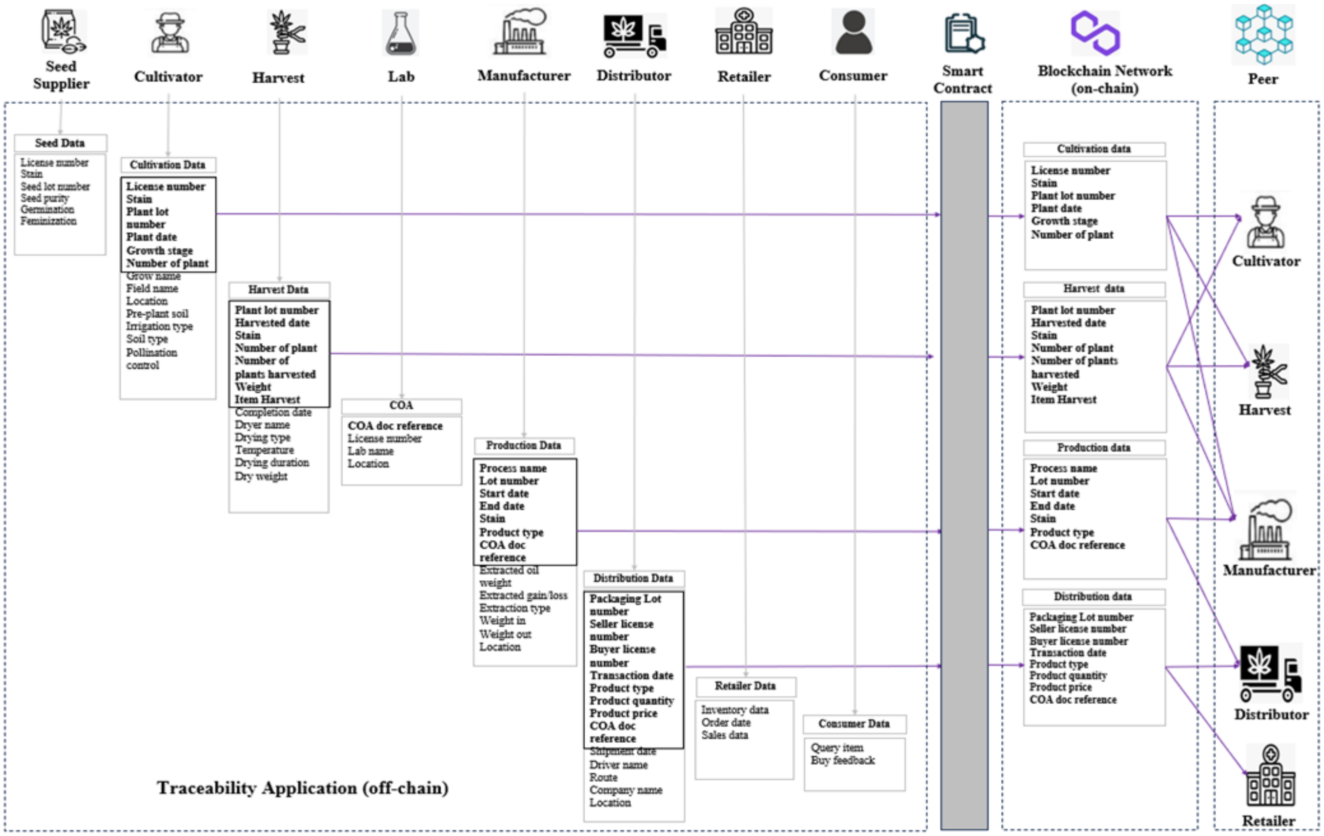

Fig. 4. Data flow diagram.

C. Sequence Diagram

Fig. 5 depicts the interaction between various supply chain actors within the proposed system, broken down into the following three stages.

- Cultivation and Harvest: A cultivator begins the plant lot, uploads it to the blockchain, and then declares an event to all peers, such as cultivator, harvest, and manufacturer. The cultivator updates the growth status, and the image of the license can be uploaded into the blockchain. The plant lot is transported to the harvesting phase when the blockchain is updated with harvest information. All transactions are retained on the blockchain, and the blockchain communicates the hash ID to the data storage.

- Production and Distribution: A company submits the Thai FDA a request for permission before starting production. As soon as the Thai FDA authorizes the request, the producer enters the manufacturing lot into the blockchain and declares an event to all peers, such as manufacturer and distributor. The manufacturer uploads photographs of the manufacturing lot to the blockchain, which then sends a hash ID to data storage so that authorized users may view the images in the future. The production batch is sent to the distributor for packing.

- Retailer and Consumer: Finally, interaction takes place between the retailer and the consumer. Thus, the retailer initiates the contract and purchases the product from the distributor, and this is declared to the peers such as the retailer, distributor, and consumer. The cannabis product is sold to the retailer and subsequently to the consumer. This process ensures that all transactions are documented and accessible to all participants within the supply chain, thereby validating the authenticity and legality of products based on the chronological sequence of events.

D. Comparison of Proposed Solution

This section compares the suggested approach for cannabis supply chain traceability with the conventional solution.

Table II provides an overview of this study. Importantly, the decentralization of the proposed system precludes any one organization from influencing or changing the data. Furthermore, the proposed solution has valuable features, providing security, transparency, credibility, and immutability. Blockchain-based traceability is offered as the proposed solution.

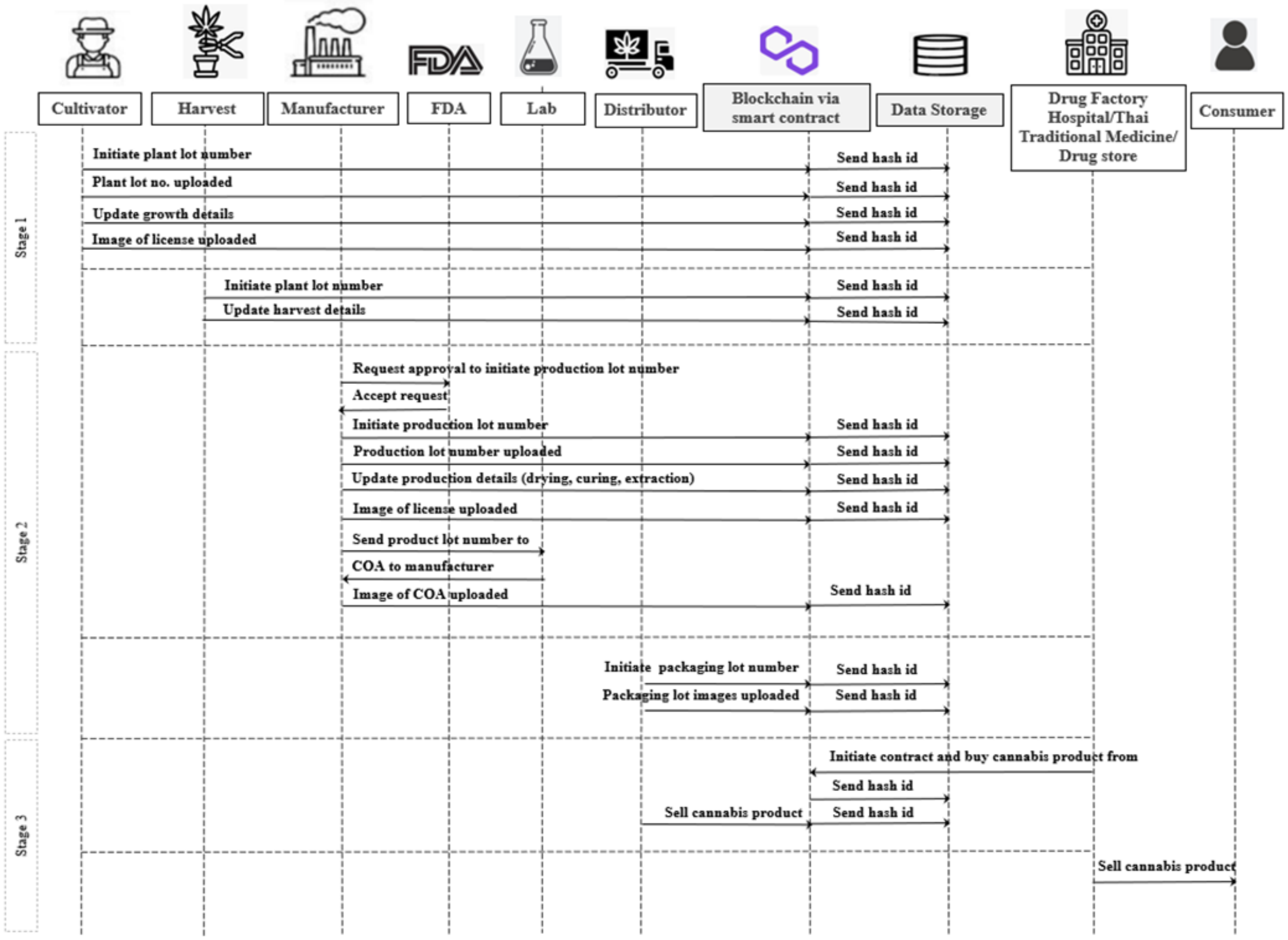
Cultivator
Harvest
Manufacturer
FDA
FDA
Lab
Distributor
Blockchain via smart contract
Data Storage
Drug Factory Hospital/Thai Traditional Medicine/ Drug store
Consumer
Stage 1
Initiate plant lot number
Send hash id
Plant lot no. uploaded
Send hash id
Update growth details
Send hash id
Image of license uploaded
Send hash id
Initiate plant lot number
Send hash id
Update harvest details
Send hash id
Stage 2
Request approval to initiate production lot number
Accept request
Initiate production lot number
Send hash id
Production lot number uploaded
Send hash id
Update production details (drying, curing, extraction)
Send hash id
Image of license uploaded
Send hash id
Send product lot number to
COA to manufacturer
Image of COA uploaded
Send hash id
Initiate packaging lot number
Send hash id
Packaging lot images uploaded
Send hash id
Stage 3
Initiate contract and buy cannabis product from
Send hash id
Sell cannabis product
Send hash id
Sell cannabis product

Fig. 5. Sequence diagram between stakeholders.

TABLE II. COMPARISON OF THE SUGGESTED AND CONVENTIONAL APPROACHES

	Proposed Solution	**Traditional Traceability System**
Data Storage	Decentralization	Centralization
Data Security	High	Low
Data Transparency	High	Low
Data Credibility	High	Low
Data Immutability	High	Low

The proposed solution uses the Polygon blockchain, which is comparable with other blockchains such as Ethereum and Hyperledger Fabric [40], as presented in Table III. Polygon is a permissionless public blockchain with excellent scalability. The average Polygon transaction fee (gas price) is less than Ethereum, according to the Polygon and Ethereum gas price [41] on May 7, 2023. In addition, data are stored on-chain in all solutions, but the suggested solution includes an extra feature that enables data to be stored off-chain as well. In conclusion, the suggested system includes several programmable smart contract languages.

TABLE III. COMPARISON BETWEEN THE PROPOSED APPROACH AND EXISTING DISTRIBUTED BLOCKCHAIN PLATFORMS

	Polygon	**Ethereum**	**Hyperledger-Fabric**
Type of Blockchain	Public Permissioned	Public Permissioned	Private Permissioned
Scalability	High	Low	Meduim
Average Transaction Fee	<$0.08	<$35.00	No
Monthly Fee	No	No	>$99.00
Native Token	MATIC	ETH	No
Off-Chain Storage	Yes	Yes	No
Programming Language	Golang, Solidity, Vyper, Python	Solidity	JavaScript, Java, Golang, Python

IV. PROPOSED BLOCKCHAIN-BASED CANNABIS TRACEABILITY IMPLEMENTATION

Using the Polygon blockchain platform, the suggested solution is constructed. Polygon is permission less public blockchain, meaning that anybody may access it. The smart contract is scripted in Python and subjected to testing within Visual Studio Code following its development. It is a web-based online environment for authoring and running smart contract code, offering users the capability to debug and test the environment of the solidity code.

A. Implementation Framework

This section discusses the five algorithms of the cultivation lot, the harvest lot, the production lot, sales data and read lot that define the operation of the proposed blockchain-based solution. First, the cultivator initiates the plant lot number and then updates the growth details in the blockchain.

Algorithm 1 describes uploading the cultivation lot number into a blockchain. The inputs for this algorithm include a license number for the cultivator, a unique identifier for the plant lot, the strain name or ID, the date the plants were planted, the current growth stage of the plants, and the number of plants in the lot. First, the cultivation record is created in Cantrak, which is a system for tracking cannabis cultivation. The record includes all the input variables provided. Next, the cultivation record is written into the blockchain, which is a secure and tamper-resistant distributed database. The blockchain ensures that the cultivation record cannot be altered or deleted once it has been written. A hash ID is generated to uniquely identify the cultivation record in the blockchain. Finally, the hash ID is printed to confirm that the cultivation record has been successfully written into the blockchain. This algorithm can be used by cultivators to securely store their cultivation lot numbers and related information on the blockchain for verification purposes.

Algorithm 1 Uploading the cultivation lot number to the blockchain

```
Input:
// Define input variables
license_number = [string]  // license number of the cultivator
lot_number = [string]  // unique identifier for the lot of plants
strain = [string]  // strain name or ID
planted_date = [string]  // date the plants were planted
growth_stage = [string]  // current growth stage of the plants
(e.g., vegetative, flowering)
number_of_plants = [integer]  // number of plants in the lot
// Create cultivation record in Cantrak
cultivation_record = {
  "license_number": license_number,
  "lot_number": lot_number,
  "strain": strain,
  "planted_date": planted_date,
  "growth_stage": growth_stage,
  "number_of_plants": number_of_plants
}
// Write cultivation record to blockchain
hash_id = blockchain.write_data(cultivation_record)
Output:
// Print hash ID for confirmation
Print ("Cultivation record successfully written to the
blockchain with hash ID:", hash_id)
End
```

Algorithm 2 describes the design to upload the harvest lot number into the blockchain. The inputs for this algorithm include a unique identifier for the plant lot, the date the plants were harvested, the specific strain of cannabis, the number of plants harvested, the weight of the harvested material, and part of the plant harvested. First, the harvest record is created in Cantrak, including all the input variables provided. Next, the harvest record is written into the blockchain, a secure and tamper-resistant distributed database. The blockchain ensures that the harvest record cannot be altered or deleted once it has been written. A hash ID is generated to uniquely identify the harvest record on the blockchain. Finally, the hash ID is printed to confirm that the harvest record has been successfully written into the blockchain. This algorithm can be used by cultivators to securely store their harvest lot numbers and related information on the blockchain for verification purposes.

Algorithm 2 Upload the harvest lot number to the blockchain

```
Input:
// Define input variables
plant_lot_number = [string]  // unique identifier for the plant lot
harvested_date = [string]  // date the plants were harvested
strain = [string]  // the specific strain of cannabis
num_plants_harvested = [int]  // number of plants harvested
weight = [float]  // weight of harvested material
item_harvested = [string]  // the part of the plant that was
harvested
// Create harvest record in Cantrak
harvest_record = {
  “plant_lot_number”: plant_lot_number,
  “harvested_date”: harvested_date,
  “strain”: strain,
  “num_plants_harvested”: num_plants_harvested,
  “weight”: weight,
  “item_harvested”: item_harvested
}
// Write the harvest record on the blockchain
hash_id = blockchain.write_data(harvest_record)
Output:
// Print hash ID for confirmation
Print (“Harvest record successfully written to the blockchain
with hash ID:”, hash_id)
End
```

Algorithm 3 describes the process for uploading the production lot number to a blockchain. The inputs for this algorithm include the name of the process (e.g., drying, curing, extraction), a unique identifier for the production lot, the date the production process started, the date the production process ended, the specific strain of cannabis being produced, type of product being produced, and the address of the uploaded Certificate of Analysis (COA) document containing THC% & CBD%. First, the production lot record is created in Cantrak, including all of the input variables provided, such as the reference for the COA document. Next, the production lot record is written into the blockchain, a secure and tamper-resistant distributed database. The blockchain ensures that the production lot record cannot be altered or deleted once it has been written. A hash ID is generated to uniquely identify the production lot record on the blockchain. Finally, the hash ID is printed to confirm that the production lot record has been successfully written into the blockchain. This algorithm can be used by cannabis producers to securely store their production lot numbers and related information on the blockchain for verification purposes. The uploaded COA document can also be easily accessed and verified through the reference address provided in the production lot record.

Algorithm 3 Upload the production lot number to the blockchain

```
Input:
// Define input variables
process_name = [string]  // name of the process (e.g., drying,
curing, extraction)
lot_number = [string]  // unique identifier for the production lot
start_date = [string]  // date the production process started
end_date = [string]  // date the production process ended
strain = [string]  // the specific strain of cannabis being
produced
product_type = [string]  // the type of product being produced
(e.g., dried flower, oil, concentrate)
coa_doc_reference = [string] // address of uploaded coa
document containing thc% & cbd%
// Create production lot record in Cantrak
production_lot_record = {
  “process_name”: process_name,
  “lot_number”: lot_number,
  “start_date”: start_date,
  “end_date”: end_date,
  “strain”: strain,
  “product_type”: product_type
  “coa_doc_reference”: coa_doc_reference
}
// Write production lot record to blockchain
hash_id = blockchain.write_data(production_lot_record)
Output:
// Print hash ID for confirmation
Print (“Production lot record successfully written to blockchain
with hash ID:”, hash_id)
End
```

Algorithm 4 describes uploading *sales data* to a blockchain. It takes several input variables, including the seller’s and buyer’s license numbers, date of the transaction, type and quantity of the product being sold, price per unit, and the reference for a COA document containing information about the product’s THC and CBD content. The algorithm creates a sales record in Cantrak, including all the input variables, and is then written into the blockchain, generating a hash ID that serves as a unique identifier for the record. Finally, the algorithm prints the hash ID for confirmation, indicating that the sales record has been successfully written into the blockchain.

Algorithm 4 Upload the sales data to the blockchain

```
Input:
// Define input variables
seller_license_number = [string]  // license number of the seller
buyer_license_number = [string]  // license number of the
buyer
transaction_date = [string]  // date the transaction occurred
product_type = [string]  // the type of product being sold (e.g.,
dried flower, oil, concentrate)
product_quantity = [float]  // quantity of product being sold
product_price = [float]  // price of the product per unit
coa_doc_reference = [string] // address of uploaded coa
document containing thc% & cbd%
// Create sales record in Cantrak
sales_record = {
  “seller_license_number”: seller_license_number,
  “buyer_license_number”: buyer_license_number,
  “transaction_date”: transaction_date,
  “product_type”: product_type,
  “product_quantity”: product_quantity,
  “product_price”: product_price
  “coa_doc_reference”: coa_doc_reference
}
// Write sales record to blockchain
hash_id = blockchain.write_data(sales_record)
Output:
// Print hash ID for confirmation
Print (“Sales record successfully written to blockchain with
hash ID:”, hash_id)
End
```

Algorithm 5 describes the reading of a *lot number* to the blockchain. This algorithm is designed to retrieve data from the blockchain using a unique lot number as input. It is typically used for tracking the cannabis cultivation process. The algorithm fetches data associated with a specific lot number from the blockchain and displays such data if found. It checks for the existence of data relating to the lot number and prints the details if data are available.

Algorithm 5 Read lot number to the blockchain.

```
Input:
// Define input variables
lot_number = [string]  // unique identifier for the lot of plants
// Fetch data from the blockchain using the entered lot number
fetched_data = blockchain.fetch_data(lot_number)
Output:
// Check if data was found
if fetched_data is empty
  // No data found for the entered lot number
  print("No data found for the entered lot number.")
else
  // Display the fetched data
  print("Data for Lot Number:", lot_number)
  print("----------------------------------------")
  print("Process Name:", fetched_data["process_name"])
  print("Start Date:", fetched_data["start_date"])
  print("End Date:", fetched_data["end_date"])
  print("Strain:", fetched_data["strain"])
  print("Product Type:", fetched_data["product_type"])
  print("COA Doc Reference:", fetched_data["coa_doc_reference"])
  // You can continue displaying other fields as needed
End
```

V. Results

The smart contract is coded in Python and validated through testing in Visual Studio Code once it is constructed. Additionally, an online web-based development environment is utilized for creating and executing programs related to smart contracts. This platform also has facilities for debugging and testing the solidity code’s surroundings.

This section presents a cost evaluation of the Polygon smart contract code. When executing a transaction on the Polygon blockchain, it is important to take into account the gas cost linked with its transmission. The experimental indoor cultivated condition covers a 100 m^2 area with four crops per year. All transactions are simulated according to the sequence diagram in Fig. 5.

TABLE IV. Cost Estimate of the Smart Contract Code for Polygon

Function Name	Transaction	Polygon Gas	Storage Cost	Cost (USD)/Yr.
Cultivation Lot	20800	1664	300	1964
Harvest Lot	10400	832	150	982
Production Lot	31200	2496	450	2946
Sale Data	20800	1664	300	1964

The smart contract uses gas for its different functions, the cost of which is converted into fiat currency (USD) in Table IV. The average Polygon gas price is US$ 0.08, according to the Polygon gas price [41] on May 7, 2023. The manufacturing lot conducted by the smart contract owner (manufacturer) is the most expensive of the four functions. This unusually large cost may be explained by the function needing data storage having six distinct variables. The cultivation lot and sale figures, respectively, represent the second and third greatest expenses.

TABLE V. Transaction Speed for Polygon

Function Name	Transaction Speed (sec)	S.D.
Cultivation Lot	20.20	8.13
Harvest Lot	17.57	3.81
Production Lot	17.20	4.33
Sale Data	19.26	9.59

The performance of the system is tested on the Polygon blockchain network (Standard Polygon speed selection) through use cases and receives performance test results, including transaction speed. The test results of the four functions are shown in Table V. The manufacturing lot is the fastest transaction. The harvest lot and sale data, respectively, represent the second and third speedy transaction.

VI. Discussion

This section examines the extension of the planned Polygon blockchain-based solution and constraints for cannabis supply chain traceability.

The proposed approach demonstrates the potential use of blockchain technology to enhance the traceability of the cannabis supply chain. Similar research has been conducted on the agricultural food (agri-food) supply chain. Even if the information is secure and transparent, it cannot be used by the cannabis sector due to its diverse procedures and complicated organizational structures. In conjunction with healthcare goods, these impacts are not only harmful to persons but also pose a substantial threat to the economy and society. The cannabis supply chain differs from others by emphasizing the identification of strains and THC/CBD ratios [1]. In addition, there are no worldwide guidelines for the traceability of agri-food research. For instance, blockchain-based traceability in medicine supply chain management [25, 42] includes a procedure distinct from cannabis and prioritizes enhanced data security protection to ensure the pharmaceuticals are genuine. Transparency from upstream to downstream still requires decentralized traceability and supply chain efficiency.

The decentralized application may be used in the storage mode of a blockchain-based traceability system for cannabis goods and includes a distributed database containing traceability information under on-chain circumstances. After uploading traceability data, the system classifies the data. The public information of the product is stored within the local database. As seen in Fig. 3, the encrypted ciphertext along with the hash ID for the public information is uploaded onto the blockchain and communicated to associated databases.

The sequence diagram may be used to convey several relationships to cannabis stakeholders. It will be necessary to add the smart contract and specify its interaction with the other entities. Another option is the simultaneous development of many goods, which necessitates an expansion of the functionalities to suit the extra products; this may be accomplished by altering the current smart contract.

This research contributes to the academic field by leveraging existing knowledge to expand and generate new insights into developing a decentralized application for the cannabis traceability process within blockchain-based supply chain management. The emphasis is on enabling trust, transparency, data security, and efficiency in cannabis supply chain management on the blockchain platform. The achievement of these objectives involves architectural design, algorithm development, sequence diagram design, and the creation of blockchain applications. Additionally, this research aims to enhance supply chain management to align with modern standards in the Industry 4.0 era, incorporating IoT technology and smart contracts. This includes ensuring transparency, real-time verification, transaction security, and meeting customer demands for the visibility and traceability of cannabis products throughout the entire supply chain.

This research focuses on developing trust in cannabis traceability using a blockchain platform to make data trustworthy, transparent, secure, and efficient. The blockchain’s consensus mechanism ensures data cannot be altered by using a timestamped, distributed database and decentralizing. This mechanism is crucial in preventing questionable products from entering the legal market, emphasizing the importance of traceability for identifying and disposing of potentially hazardous products. The flexibility introduced by storing data from the cannabis traceability system on-chain and off-chain reduces the loading pressure on blockchain and storing necessary information. Moreover, scalability in developing a blockchain-based traceability process avoids delays and high transaction fees to establish sustainability for the cannabis industry.

Finally, the algorithms are developed in easy stages and may be implemented inside the application for the cannabis supply chain.

VII. Conclusion

This research examines the difficulty of cannabis supply chain traceability and its relevance, particularly in terms of identifying the source to make the product look authentic. It proposes a Polygon blockchain-based strategy for the cannabis supply chain that offers data security, immutability, and decentralized control over cannabis extract products.

The suggested approach leverages a smart contract capable of processing a variety of transactions among cannabis supply chain stakeholders to accomplish the automatic documentation of occurrences that are accessible to all involved parties. The blockchain-based solution includes on-chain and off-chain storage, algorithms, and a sequence diagram. This research reveals that the various smart contract functionalities are responsible for the transaction’s cost-effectiveness in terms of the quantity of gas used. The scalability of the blockchain-based solution is necessary for the sustainable cannabis industry.

Finally, the researchers plan to continue their efforts to enhance the international standards for traceability, the supply chain management to align with modern standards in the industry 4.0 eras, and the efficiency of the cannabis supply chain process in future work.

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Predictive Modeling of Kuwaiti Chronic Kidney Diseases (KCKD): Leveraging Electronic Health Records for Clinical Decision-Making

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***Abstract*—Chronic kidney disease (CDK) represents a significant public health concern globally, and its prevalence is on the rise. In the context of Kuwait, this study addresses the imperative of predicting CKD by leveraging the wealth of information embedded in electronic health records (EHRs). The primary objective is to develop a predictive model capable of early identification of individuals at risk for CKD, thereby enabling timely interventions and personalized healthcare strategies and equip clinicians with information that enhances their ability to make well-informed decisions regarding prognoses or therapeutic interventions. In this study, a dataset has been created from Kuwaiti healthcare institutions, emphasizing the richness and diversity of patient information encapsulated in EHRs and a feature engineering step has been applied for labeling it. Various ensemble learning algorithms, Ada Boost, Extreme Gradient Boosting, Extra Trees, Gradient Boosting, Random Forest, and various single learning algorithms, Decision Tree, K-Nearest Neighbors, Logistic Regression, Multilayer Perceptron, Stochastic Gradient Descent, Support Vector Machines, have been implemented. By examining the empirical findings of our tests, our results showcase the models' capability to identify individuals at risk for CKD at an early stage, facilitating targeted healthcare interventions. Decision Tree was the best classifier achieving 99.5% accuracy and 99.3% macro averaged f1-score.**

Keywords*—Chronic kidney diseases; Electronic Health Records (EHR); classification; machine learning

I. Introduction

The digitalization of patient health records has brought about a new era in healthcare, one that offers previously unheard-of possibilities for data-driven research and medical improvements [1]. With the right use, Electronic Health Records (EHR) can become a veritable gold mine of detailed, longitudinal patient data. With the right application, this data can revolutionize the way to anticipate and prevent disease. A major obstacle confronting the healthcare sector is the increasing prevalence of chronic diseases, which contribute significantly to worldwide morbidity and mortality [2]. A growing number of people are interested in using the potential of EHR to create strong predictive models that target early identification, risk assessment, and tailored intervention for chronic diseases. Millions of people worldwide suffer from CKD, a widespread, frequently silent illness that places a heavy burden on healthcare systems around the globe. Innovative methods for identifying those at risk are desperately needed as the frequency of CKD rises, as this will allow for early intervention and individualized care. In this quest, EHRs, which comprise an extensive patient data repository, proves to be a vital asset. They provide a dynamic platform for the creation of predictive models that have the potential to revolutionize the management CKD [3].

When it comes to identifying subtle signs and patterns that precede overt clinical symptoms, traditional diagnostic techniques frequently fall short. Within this framework, EHRs function as a repository for longitudinal patient data, encompassing test findings, medication records, and demographic details, offering a comprehensive perspective of a person's medical journey. By using EHR data, it is possible to identify complex patterns and risk factors related to CKD, which can lead to tailored interventions that can be implemented in a timely manner [3].

In earlier research [4], the same authors suggested using EHRs instead of paper ones to record patients' health information. Also, they highlighted the application of predictive analytics models, which use electronic health data to predict the emergence of chronic diseases early on. According to this study, CKD affects around 700 million people globally each year, and it causes nearly 1.2 million fatalities [4]. The current research contributes to improve the quality of life for those with or at risk of CKD in Kuwait by highlighting the revolutionary potential of predictive ensemble learning and single learning algorithms models using actual Kuwaiti EHRs which are collected from hospitals and health institutes in Kuwait and altering clinical workflows and resource allocation.

Through patient follow-up, changes in several clinical markers could be seen over time and their relationship to the course of the disease. By using this method, we may record the time dynamics and find any patterns or trends that might point to deteriorating CKD. While our study primarily focused on the development and validation of the predictive model, we acknowledge the importance of discussing the practical aspects of its clinical implementation. Addressing issues related to data integration, workflow adaptation, and acceptance by healthcare professionals is critical for the effective deployment of predictive models in routine clinical care.

The following are the primary contributions of the article:

- Using electronic health records instead of paper records.
- Using accessible datasets from patients' medical records, machine learning techniques are used to predict the existence of chronic illnesses.
- Examining medical records of all patients to ensure proper diagnosis of chronic disorders.
- Identifying new patients with comparable symptoms and illness development phases based on physician supervision and medical record analysis for a specific type of chronic disease.

The latter part of the manuscript will delve into related research in Section II, followed by an examination of the datasets employed in this study in Section III. Section IV will provide a comprehensive description of the proposed technique. Subsequently, Section V will present the test results and evaluate the effectiveness of the proposed strategy. Lastly, Section VI and Section VII will present the discussion and conclusions respectively.

II. Related Work

Considerable work has been done to anticipate CKD. This section will include descriptions of a few of these works.

To predict CKD using clinical data, Ekanayake and Herath [5] investigated the use of machine learning techniques. They noted the need of feature engineering, handling missing values, and integrating domain knowledge in the study. They presented a procedure that includes attribute selection, handling of missing values, and data preprocessing. The application of a KNN-based technique to handle missing values in datasets pertaining to several diseases was also taken into consideration in this work. According to the study, the random forest and extra trees classifiers produced the best results for predicting CKD, obtaining 100% accuracy for both training and testing. Furthermore, the study made no mention of any potential privacy or ethical issues with using patient data for predictive modeling.

Q. Bai et al. [6] developed a predictive model for end-stage kidney disease (ESKD) using a dataset of 748 people with chronic kidney disease (CKD). To manage missing data, the authors used a five-set multiple imputation method. They then examined each model's performance on each imputed set, combining the findings to get the result. At 81%, the random forest algorithm produced the best overall performance as determined by the AUC score. On the other hand, the Kidney Failure Risk Equation (KFRE) model, which is based on three straightforward variables, showed the highest accuracy, specificity, and precision along with equivalent AUC scores. The research found a void in the literature about the applicability of predictive models for ESKD in other ethnic groups, including the Chinese population. It also brought attention to the possibility of predicting ESKD without the need for urine testing, which could result in a more straightforward model with comparable reliability. The KFRE model's default threshold sensitivity and the lack of previous attempts to use machine learning techniques to predict the occurrence of ESKD in CKD patients are among the study's shortcomings.

Y. Zhu et al. [7] presented a unique method utilizing longitudinal patient Electronic Health Records (EHRs) to predict the course of CKD. They forecasted the course of CKD with impressive accuracy by combining an AI prediction model with an EHR preprocessing pipeline. Preprocessing the EHR incorporates multiple clinical factors and transforms them into time series data that may be used in Recurrent Neural Network (RNN) modeling. Their main goal was to forecast how quickly CKD will advance from early to late stages. Feature vectors that represent patient data prior to a given period are analyzed for each case patient. Based on patient race, sex, age, and duration of time series, control patients are matched when utilizing the time series of a single variable, eGFR, the RNN model predicts disease development within a year with an average AUROC of 0.957. Due to patient privacy issues and the proprietary nature of the data, there is a research gap in the lack of publicly available datasets.

H. Nayeem et al. [8] applied machine learning approaches to predict chronic kidney disease (CKD). The 400 examples in the sample comprise 25 attributes total one dependent attribute and 24 independent attributes. To predict CKD, the study used methods from Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN). An analysis of the classifiers' comparative performance revealed that ANN performed better than the other techniques, achieving 98.6% and 98% accuracy and f1-score, respectively. The study failed to examine the possibility of biases in the dataset or the applicability of the results to different groups with chronic kidney disease.

D. Chicco et al. [9] examined CKD and found independent risk factors linked to stages 3-5 of the disease by examining a dataset of 491 individuals from the United Arab Emirates. The authors used two different methodologies, one based on machine learning techniques and the other on conventional univariate biostatistics testing. The results of the biostatistical tests showed that while 68.42% of the clinical parameters were significant, they were not precise. As a result, the writers ranked features using Random Forests. The study showed that, independent of temporal information, computational intelligence could predict the development of severe CKD, suggesting that the significance of clinical factors changes when the temporal component is considered. The study is significant because it uses machine learning to uncover critical clinical traits while thoroughly examining risk factors linked to CKD at stages 3-5. Remarkably, the study concentrated on developing and enhancing computational intelligence technologies rather than discussing the therapeutic implications of the results.

In another study on the prediction of chronic renal illness, S. Pal [10] used three machine learning classifiers: Support Vector Machine (SVM), Decision Tree, and Logistic Regression. After the classifiers were assessed, it was discovered that the Decision Tree classifier performed the best, obtaining 95.92% accuracy, 0.99 precision, 0.98 recall, and

0.98 F1-score. To enhance the performance of the base classifiers, bagging ensemble methods were also used in this study. The Decision Tree classifier achieved the greatest accuracy of 97.23%. There may be a research gap because the study did not specify the precise dataset that was utilized to train and test the classifiers.

M. Klamrowski et al. [11] used machine learning to create a prediction model for individuals with advanced chronic renal disease who are at risk of short-term kidney failure. They were intended to be integrated into electronic medical records for clinical use, and they made use of dynamic laboratory data to increase prediction accuracy. They showed that the prediction of short-term kidney failure requires the inclusion of more current follow-up data, especially dynamic lab data. The study also demonstrated how the prediction model may be used to lower the rates of unscheduled dialysis and the negative consequences that are linked with it. The study found that using machine learning methods, such as Cox regression, to take into consideration the complex interrelationships and complexity of the data was the best approach. This study found a knowledge gap on the requirement to increase the generalizability of prediction models to various populations. Furthermore, there is a lack of validating the prediction model's efficacy within the typical renal disease clinic workflow and integration of the model into clinical practice.

A. Islam et al. [12] used machine learning techniques to forecast chronic kidney disease (CKD) in its early stages. To minimize the number of features and get rid of unnecessary data, relationships between various aspects were investigated and the models were trained and validated using input parameters. After preprocessing the dataset, principal component analysis (PCA) was used to determine which features were most important in CKD detection. This study discovered that, after using a filter feature selection approach, hemoglobin, albumin, and specific gravity had the greatest influence on CKD prediction. The best approach involved using machine learning algorithms to predict CKD at an early stage, with a focus on identifying the most dominant features for detecting the disease. The performance of the proposed model was evaluated, and it was suggested that CKD risk factor predicting could be used to identify individuals at risk within the community without the need for hospital admission. The challenge of locating a different dataset with comparable properties for a useful comparison was noted by the authors.

III. Data

In this study, an EHR dataset comprising information about patients in Kuwaiti hospitals was constructed. Each row in the dataset represents a single patient, and the columns indicate all the patient's attributes (laboratory analysis), as detailed in Table I. This dataset was created for the purpose of predicting Kuwaiti Chronic Kidney Diseases (KCKD) by combining all characteristics from original datasets into a single csv file for use in training and testing prediction models, in addition to the personal information of all patients during all hospital visits. This EHR dataset has been acquired from the Department of Health Studies and Research at the Kuwaiti Ministry of Health to get clearance to access medical data and publish under the supervision of National Center for Health Information, and the Department of Prevention and Control of Non-Communicable Diseases in Kuwait. Data authorization has been obtained from the director of Al-Adan Hospital and forward the Request to the appropriate departments. Obtain clearance from the heads of the Medical Board, the Department of Clinical Radiology, the Department of Medical Laboratories, and the Department of Information Systems at Al-Adan Hospital for various departments. The dataset is available on Kaggle, KCKD, in the final version after feature engineering process. Another online labeled CKD dataset with the same features has been used for labeling the first one using feature engineering process that will be discussed in the next section. For the findings of this study to be applicable and generalizable to a wide range of populations, we must take ethnic and cultural heterogeneity into account in our research. We can evaluate potential differences in illness susceptibility, progression trends, and response to therapies by stratifying our dataset according to ethnicity or cultural background. Furthermore, our predictive models may be more accurate and relevant for demographic groups if pertinent cultural determinants of health are included.

TABLE I. Name and Type of each Feature of the EHR Dataset

Feature Name	Type
Potassium	Numeric
Sodium	Numeric
CL	Numeric
Ceriatinin	Numeric
Blood Urea	Numeric

IV. Methodology

In this section, the methodology of the proposed work will be represented and provide an explanation for every step. Fig. 1 represents the block diagram of the proposed work and steps including two phases.

A. Feature Engineering

This paper introduces a feature engineering approach [13] for kidney disease classification, focusing on leveraging known features from a labeled dataset to enhance predictive modeling on an unlabeled dataset. The methodology involves meticulous extraction and refinement of relevant features, employing preprocessing techniques to ensure data quality, and training multiple machine learning [14] classification algorithms. The best-performing model is then selected based on cross-validation results on the labeled dataset. Subsequently, this chosen model is applied to predict classes for the unlabeled dataset, providing a seamless transfer of knowledge between labeled and unlabeled data. The paper concludes with an analysis of the model's performance, highlighting the efficacy of the proposed feature engineering process in improving the accuracy and generalization of kidney disease classification.

B. Data Preprocessing

Preprocessing steps are crucial for kidney datasets as they play a vital role in enhancing the quality of the data and ensuring that machine learning models can effectively learn patterns and make accurate predictions. Here are some key preprocessing steps and their importance for kidney datasets.

1) Handling missing value: Kidney datasets may often have missing values due to various reasons such as incomplete sample collection or laboratory errors. Imputing or handling missing values is critical to maintain the integrity of the dataset and ensure that the analysis is based on as much relevant information as possible. By checking for null values in the aggregated dataset we noticed that there are some missing values in the input features as shown in Table II.

TABLE II. NUMBER OF NULL VALUES IN THE AGGREGATED DATASET

Feature Name	# Null values	# All records
Blood Urea (mgs/dL)	14	680
Serum Creatinine (mgs/dL)	12	
Sodium (mEq/L)	67	
Potassium (mEq/L)	68	

2) Normalization / Scaling: Different features in the dataset may have different scales. Normalizing or scaling features, especially numeric ones like blood pressure or serum creatinine, helps in bringing them to a similar scale, preventing certain features from dominating others during model training. We utilized the Standard Scaler [2] during preprocessing for the kidney dataset. This technique normalizes features to have a mean of 0 and a standard deviation of 1, ensuring uniform scales and enhancing the effectiveness of machine learning models, especially those reliant on distance measures.

3) Data splitting: In the experimentation of this study, for the aggregated dataset, we divided the aggregated kidney dataset into training (85%) and testing (15%) sets. This resulted in 571 instances for training and 101 instances for testing, out of the total 672 instances in the dataset. After labeling the second dataset, we divided it into two portions 80% (1600 samples) for training and 20% (401 samples) for testing as shown in Table III. This approach ensures a comprehensive evaluation of model performance, balancing training, and testing for reliable insights into the effectiveness of the proposed models for kidney disease classification.

TABLE III. NUMBER OF INSTANCES IN AGGREGATED CKD AND KCKD DATASETS

Dataset	Split ratio		Training instances	Testing instances	Total instances
Aggregated Dataset	85% Train	15% Test	571	101	672
Dataset after labeling	80% Train	20% Test	1600	401	2001

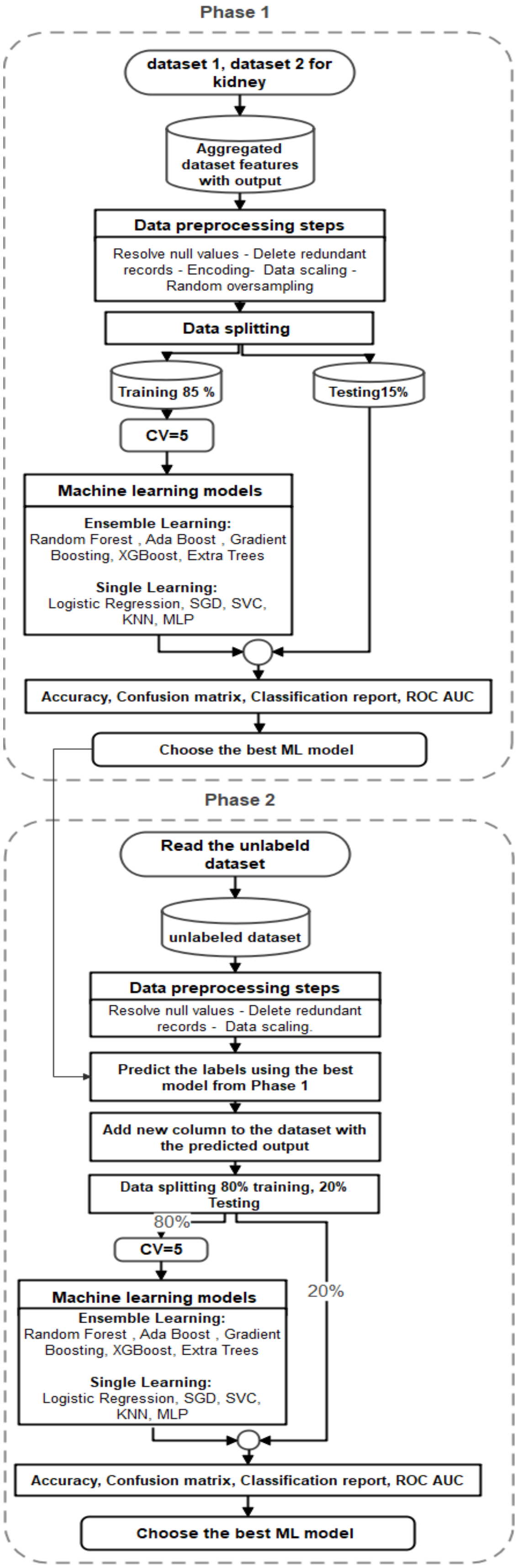
Phase 1
dataset 1, dataset 2 for kidney
Aggregated dataset features with output
Data preprocessing steps
Resolve null values - Delete redundant records - Encoding- Data scaling - Random oversampling
Data splitting
Training 85 %
Testing15%
CV=5
Machine learning models
Ensemble Learning:
Random Forest , Ada Boost , Gradient Boosting, XGBoost, Extra Trees
Single Learning:
Logistic Regression, SGD, SVC, KNN, MLP
Accuracy, Confusion matrix, Classification report, ROC AUC
Choose the best ML model
Phase 2
Read the unlabeld dataset
unlabeled dataset
Data preprocessing steps
Resolve null values - Delete redundant records - Data scaling.
Predict the labels using the best model from Phase 1
Add new column to the dataset with the predicted output
Data splitting 80% training, 20% Testing
80%
CV=5
20%
Machine learning models
Ensemble Learning:
Random Forest , Ada Boost , Gradient Boosting, XGBoost, Extra Trees
Single Learning:
Logistic Regression, SGD, SVC, KNN, MLP
Accuracy, Confusion matrix, Classification report, ROC AUC
Choose the best ML model

Fig. 1. Proposed method architecture.

TABLE IV. NUMBER OF INSTANCS BEFORE AND AFTER OVER SAMPLING IN THE AGGREGATED DATASET AND NEW DATASET

Dataset	Label	# samples before balancing	# samples after balancing
Aggregated Dataset	non-CKD	216	355
	CKD	355	355
Dataset after labeling	non-CKD	345	1255
	CKD	1255	1255
Total		2171	3220

Table IV displays the impact of oversampling on instance counts in both the Aggregated Dataset and new labeled dataset after feature engineering. In the Aggregated Dataset section, the initial counts show 216 instances for the "non-CKD" class and 355 instances for the "CKD" class. After balancing, both classes have 355 instances, resulting in a total of 710 instances. Moving to the dataset after labeling using feature engineering, the “non-CKD” class initially has 345 instances, while the "CKD" class has 1255 instances. Following oversampling, both classes achieve balance with 1255 instances each, contributing to a total of 2510 instances. This oversampling strategy aims to ensure a more equitable representation of classes for enhanced model training and evaluation.

4) Cross Validation (CV): To rigorously assess proposed machine learning models, we adopted a five-fold cross-validation approach [15]. This method divides the dataset into five subsets, iteratively training the model on four and testing on the remaining one. By calculating and averaging performance metrics, such as accuracy and precision, across all iterations, we obtain a robust evaluation of proposed model's generalizability. This strategy ensures reliability by preventing over-sensitivity to a particular training set composition and guides hyperparameter tuning efforts for optimized model performance.

C. Machine Learning Methods

In this study, we employed two categories of machine learning algorithms, namely ensemble learning algorithms and single learning algorithms, as outlined below.

1) Single learning: In this research, we employed a diverse set of single learning algorithms, each contributing distinct strengths to analysis. The single learning algorithms used are illustrated below.

a) Decision Tree (DT) [16]: A clever and straightforward machine learning predictive model technique called a decision tree classifier uses a tree representation to go from an item's observation to a judgment about the item's target value. The decision tree is a tool for classification, description, and generalization of a given collection of data that combines mathematics and computational techniques.

b) Logistic Regression (LR) [17]: Predicting Binary Probabilities: Logistic Regression serves as a linear classification method that predicts the likelihood of a binary outcome. It accomplishes this by fitting a logistic curve to the data, making it particularly suitable for applications like binary classification tasks such as spam detection or medical diagnoses.

c) Stochastic Gradient Descent (SGD) [18]: SGD stands out as an optimization technique widely employed in machine learning model training. It refines model parameters through iterative and stochastic updates, proving notably efficient for handling extensive datasets. SGD finds frequent use in tasks involving neural network training and other iterative optimization challenges.

d) Support Vector Classifier (SVC) [19]: Using training data at class boundaries, the SVM is a linear classifier. Radial Basis Function (RBF) kernels, which were employed in this work, sigmoid, linear, and other kernel functions are used by the SVM model to classify non-linear data. Assuming that the new sample and the existing samples are similar, the KNN algorithm assigns the new sample to the category that most closely matches the existing categories [19].

e) K-Nearest Neighbours (KNN) [20]: KNN, a straightforward yet powerful algorithm, is adept at classification and regression duties. Its principle lies in classifying data points by considering the majority class among their k-nearest neighbours. KNN's simplicity and ease of implementation make it suitable for diverse applications, ranging from recommendation systems to pattern recognition.

f) Multi-Layer Perceptron (MLP) [21]: MLP, categorized as a neural network with multiple layers, exhibits proficiency in discerning intricate patterns and relationships within datasets. This algorithm's versatility is evident across applications like image recognition, natural language processing, and speech recognition. The depth of the network facilitates the capture of intricate hierarchical features in the data.

These models operate independently, with each algorithm focusing on learning patterns and relationships within the data individually. The application of these single learning techniques allows us to harness the specific capabilities of each algorithm to enhance the understanding of the intricate dynamics within the kidney dataset.

2) Ensemble learning: To further fortify the predictive capabilities of proposed models, we incorporated ensemble learning algorithms, a category renowned for amalgamating multiple models to achieve superior performance. The ensemble learning algorithms utilized in this research encompassed the following types:

a) Random Forest [22]: Random Forest, an ensemble learning algorithm, builds numerous decision trees during training, consolidating predictions to improve reliability and mitigate overfitting. Its versatility has proven effective across diverse domains, including the focus of this research.

b) Ada Boost [23]: Ada Boost, a boosting algorithm, combines weak learners sequentially to form a robust model. Its iterative approach corrects errors from previous models, with a focus on challenging instances. In this research, Ada Boost plays a pivotal role in elevating accuracy in ensemble predictions.

c) Gradient Boosting (GBoost) [24]: Gradient Boosting, an iterative ensemble algorithm, constructs decision trees sequentially to rectify the errors of preceding trees. Known for achieving high precision, GBoost is particularly valuable in scenarios requiring accurate predictions, as exemplified in this research.

d) XGBoost [25]: XGBoost, or Extreme Gradient Boosting, represents an optimized form of gradient boosting with a focus on speed and efficiency. Its parallelized training and regularization techniques make it scalable and efficient for handling extensive datasets. In this research, XGBoost enhances the effectiveness of ensemble learning.

e) Extra Trees [26]: Extra Trees, or Extremely Randomized Trees, is an ensemble algorithm introducing additional randomization during tree construction. This intentional randomness enhances model robustness and generalization. In this research, Extra Trees contributes to the ensemble's diversity, fostering a more resilient predictive model.

Leveraging the collective wisdom of diverse models, these ensemble learning techniques aimed to amplify the robustness and accuracy of the predictions, particularly in the context of kidney disease classification.

D. Performance Metrics

In this section, we detail the evaluation metrics used in the thesis to assess the performance of statistical and machine learning algorithms, including accuracy, the confusion matrix, and the classification report.

1) Confusion Matrix: This matrix [27], a vital tool for classification model evaluation, provides a comprehensive summary of predictions versus actual labels. Comprising elements like True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), it illuminates the model's performance for positive and negative classes.

2) Classification Report: Offering a detailed assessment across different classes, the classification report presents various metrics per class. It includes equations for accuracy in Eq. (1), precision in Eq. (2), recall in Eq. (3), and F1 score in Eq. (4) derived from the report [28]:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{3}$$

$$\text{F-measure} = \frac{2 * \text{TP}}{(2 * \text{TP} + \text{FP} + \text{FN})} \tag{4}$$

3) ROC AUC Curve: Illustrating a binary classification model's performance across decision thresholds, the ROC curve [29] and its AUC metric (ranging from 0 to 1) indicate discrimination ability, with higher values denoting superior performance.

V. Experimental Results

Several experiments have been conducted to assess the proposed model. The Python programming language and various machine learning toolboxes, such as scikit-learn, imblearn, NumPy, and matplotlib, were used for all experiments, which were conducted using the Jupiter notebook editor.

As shown in Table V, a feature engineering process has been applied for an aggregated CKD dataset with the same attributes to obtain the optimal labels for new EHRs dataset. The aggregated CKD dataset has been trained using nine classifiers, five ensemble learning algorithms (Ada Boost, XGBoost, Extra Trees, GBoost, and RF) and six single learning algorithms (DT, KNN, LR, MLP, SGD, and SVM), and the highest performance was obtained by GBoost classifier, which achieved 97.7%, 97.8, 98%, and 97.8% for precision, recall, accuracy, and macro-averaged f1-score respectively. The RF classifier was in second place achieving 95.6%, 95.6%, 96%, and 95.5% for precision, recall, accuracy, and macro-averaged f1-score respectively.

After obtaining the best labels for each patient in KCKD dataset, it was ready for building the classification model with the same classifiers mentioned above, which can predict the case of patients in Kuwait hospitals, who have the same symptoms with different values.

TABLE V. TRAINING PERFORMANCE OF ALL CLASSIFIERS FOR THE AGGREGATED CKD DATASET

	Classifier	Precision	Recall	Accuracy	F1-score
Single Learning	DT	94.3%	94.9%	95.0%	94.6%
	KNN	92.2%	92.7%	93.1%	92.4%
	LR	86.5%	85.1%	87.1%	85.6%
	MLP	94.1%	90.9%	93.1%	92.2%
	SGD	87.0%	87.0%	88.1%	87.0%
	SVM	86.8%	87.6%	88.2%	87.2%
Ensemble Learning	Ada Boost	86.8%	82.6%	77.6%	74.7%
	XGBoost	**94.9%**	**94.5%**	**90.2%**	**92.6%**
	Extra Trees	81.8%	85.7%	53.6%	54.8%
	GBoost	89.9%	88.5%	68.4%	82.3%
	RF	86.8%	84.6%	71.0%	75.3%

Table VI shows the performance of all classifiers for KCKD dataset. The highest performance was obtained by DT classifier, which achieved 98.9%, 99.7%, 99.5%, and 99.3% for precision, recall, accuracy, and macro-averaged f1-score respectively. The second place for Ada Boost classifier, which we achieved 98.4%, 99.5%, 99.2%, and 98.9% for precision, recall, accuracy, and macro-averaged f1-score respectively.

A recognized confusion matrix is obtained in Table VII and Table VIII for the purpose of estimating four different measures: recall, accuracy, precision, and f-score. The confusion matrix displays the classification results as a matrix. Information for both existing and anticipated classes created with the classification framework is included. The cell shows the sample size that was mistakenly identified as false while quiet (i.e., TN) and as true when it was truly true (i.e., TP). The number of pieces that were erroneously classified is indicated by the two remaining cells.

TABLE VI. TRAINING PERFORMANCE OF ALL CLASSIFIERS FOR KCKD DATASET AFTER LABELING

	Classifier	Precision	Recall	Accuracy	F1-score
Single Learning	**DT**	**98.9%**	**99.7%**	**99.5%**	**99.3%**
	KNN	91.3%	95.1%	94.7%	92.9%
	LR	95.2%	96.5%	97.0%	95.8%
	MLP	97.4%	97.7%	98.2%	97.5%
	SGD	94.1%	96.6%	96.5%	95.3%
	SVM	91.8%	97.1%	95.5%	94.1%
Ensemble Learning	Ada Boost	98.4%	99.5%	99.2%	98.9%
	XGBoost	97.9%	96.4%	98.0%	97.1%
	Extra Trees	38.4%	50.0%	76.8%	43.4%
	GBoost	98.2%	98.9%	99.0%	98.6%
	RF	98.3%	99.2%	99.2%	98.9%

TABLE VII. CLASSIFICATION REPORTS OF SVM, DT, AND MLP CLASSIFIERS FOR AGGREGATED CKD DATASET

Dataset	Classifier	Precision	Recall	F-measure	Class
Single Learning	DT	91.89	94.44	93.15	0
		96.88	95.38	96.12	1
	KNN	89.19	91.67	90.41	0
		95.31	93.85	94.57	1
	LR	84.85	77.78	81.16	0
		88.24	92.31	90.23	1
	MLP	96.77	83.33	89.55	0
		91.43	98.46	94.81	1
	SGD	83.33	83.33	83.33	0
		90.77	90.77	90.77	1
	SVM	81.58	86.11	83.78	0
		92.06	89.23	90.62	1
Ensemble Learning	Ada Boost	96.67	80.56	87.88	0
		90.14	98.46	94.12	1
	XGBoost	89.74	97.22	93.33	0
		98.39	93.85	96.06	1
	Extra Trees	89.47	47.22	61.82	0
		76.83	96.92	85.71	1
	GBoost	97.22	97.22	97.22	0
		98.46	98.46	98.46	1
	RF	94.44	94.44	94.44	0
		96.92	96.92	96.92	1

TABLE VIII. CLASSIFICATION REPORTS OF SVM, DT, AND MLP CLASSIFIERS FOR KCKD DATASET

Dataset	Classifier	Precision	Recall	F-measure	Class
Single Learning	DT	97.89	100.0	98.94	0
		100.0	99.35	96.67	1
	KNN	93.96	95.70	89.45	0
		98.64	94.48	96.52	1
	LR	91.75	95.70	93.68	0
		98.86	97.40	98.04	1
	MLP	95.74	96.77	96.26	0
		99.02	98.70	99.86	1
	SGD	89.11	96.77	92.78	0
		99.00	96.43	97.70	1
	SVM	83.87	100.0	91.18	0
		100.0	94.16	96.99	1
Ensemble Learning	Ada Boost	96.88	100.0	98.41	0
		100.0	99.03	99.51	1
	XGBoost	97.75	93.55	95.60	0
		98.08	99.35	98.71	1
	Extra Trees	00.00	00.00	00.00	0
		76.81	100.0	86.88	1
	GBoost	96.84	98.92	97.87	0
		99.67	99.03	99.35	1
	RF	96.88	100.0	98.41	0
		100.0	99.03	99.51	1

The cells indicating the sample size labeled true when it was incorrect (i.e., FP) and false when it was true (i.e., FN). All measures were calculated using the formulas listed in the previous subsection, 2.4.2. In the class column, "1" means CKD patient and "0" means non-CKD patient.

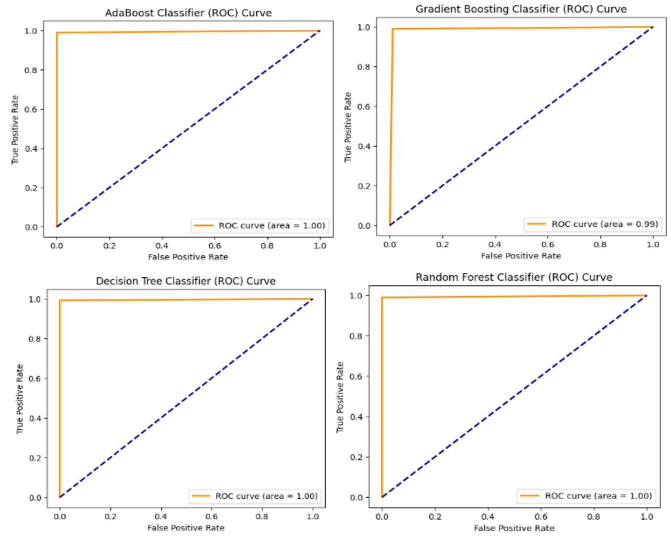

Fig. 2. ROC curve of DT, RF, AdaBoost, GBoost curve for Kuwaiti CKD, from left to right, respectively.

Fig. 2 shows the ROC curve of the best ensemble and single learning classifiers applied for Kuwaiti CKD, DT, RF, AdaBoost, GBoost.

VI. Discussion

The labeled dataset of CKD, as demonstrated in Table VI, presents a comprehensive evaluation of various classifiers, each assessed on key performance metrics including precision, recall, accuracy, and F1-score. Among these classifiers, the results distinctly highlight the exceptional performance of the Decision Trees (DT) algorithm. With a precision of 98.9%, recall of 99.7%, accuracy of 99.5%, and an F1-score of 99.3%, DT emerges as the standout performer across all metrics. The superiority of DT can be attributed to several inherent advantages it offers. Notably, its innate interpretability lends itself well to domains such as CKD, where comprehensible decision-making is crucial for clinical applications. Moreover, DT's ability to effectively capture non-linear relationships within the data proves invaluable in handling the complex patterns often present in CKD datasets. Furthermore, its robustness to irrelevant features ensures efficient feature selection, enhancing model performance and generalization. Given the scalability and efficiency of DT, particularly in managing large datasets, it emerges as not only the best-performing classifier in this evaluation but also a pragmatic choice for real-world CKD classification tasks. This robust performance underscores the utility of Decision Trees as a reliable and effective tool for medical diagnosis and decision support in the context of chronic kidney disease. We carefully selected algorithms based on their proven effectiveness for the task. Through rigorous testing, we found that our chosen ensemble and single learning algorithms consistently delivered high performance. While we acknowledge the potential for different results with alternative algorithms, our focus was on leveraging well-established methods known for their reliability. Our thorough validation process supports the confidence in the efficacy of our selected algorithms for this study. We recognize the importance of clinical interpretability in healthcare settings. While our study primarily focused on performance metrics like accuracy, precision, recall, and F1-score, we understand the need to understand model predictions. By addressing interpretability, we aim to bridge the gap between model performance and real-world healthcare applications, enhancing trust among healthcare professionals.

VII. Conclusion and Future Work

To predict KCKD, we created EHRs dataset using patients' symptoms collected from Kuwait hospitals and health institutions, a feature engineering process has been utilized for this dataset to obtain the optimal labels for each patient by training another CKD dataset with the same attributes using several ensemble learning classifiers, Ada Boost, XGBoost, Extra Trees, GBoost, RF, and several single learning classifiers, DT, KNN, LR, MLP, SGD, and SVM. The study's findings suggest that chronic disease identification and prediction can be accomplished with the help of data mining tools. According to the findings, the DT algorithm was the best option with the highest performance for predicting Kuwait CKD, achieving 99.5% accuracy and 99.3% f1-score, while the GBoost algorithm was the most effective for training the aggregated CKD dataset and obtaining the optimal labels of Kuwait CKD dataset, achieving 98% accuracy and 97.8% f1-score. Strong performance was also shown by the RF and Ada Boost algorithms on both datasets. In further work, we intend to include a portion addressing the practical issues and difficulties related to applying our predictive model in clinical settings. The predictive model's seamless integration into clinical decision-making processes, workflow adaptation to ensure healthcare professionals' acceptance and adoption of the model, and data compatibility and integration with current electronic health record systems will all be covered in this.

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Data Manipulation in Wireless Sensor Networks: Enhancing Security Through Blockchain Integration with Proposal Mitigation Strategy

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Abstract—**In recent years, Wireless Sensor Networks (WSNs) have become integral in various applications ranging from environmental monitoring to defense. However, the security and reliability of these networks remain a paramount concern due to their susceptibility to various types of cyber-attacks and failures. This paper proposes a novel integration of blockchain technology with WSNs to address these challenges. Blockchain, with its decentralized and tamper-resistant ledger, offers a robust framework to enhance the security and reliability of sensor networks. The study begins by analyzing the current security threats and challenges faced by WSNs, emphasizing the need for a solution that can ensure data integrity, confidentiality, and network resilience. We then introduce blockchain technology and discuss its key features such as decentralization, immutability, and consensus algorithms, which are beneficial in creating a secure and reliable WSN environment. Subsequently, we present a detailed architecture of how blockchain can be integrated with WSNs. This includes the deployment of a lightweight blockchain protocol suited for the limited computational resources of sensor nodes. We also explore the use of smart contracts for automated, secure data handling and network management within WSNs. To validate the proposed integration, we conduct a simulations based on network attacks. The results demonstrate significant improvements in the security and reliability of WSNs when blockchain is implemented. This is evidenced by enhanced resistance to common attacks, such as data manipulation and node compromise and increased network uptime.**

Keywords—Wireless sensor networks; blockchain technology; network security; data integrity

I. Introduction

In an era increasingly reliant on the Internet of Things (IoT), the integrity and security of data in wireless sensor networks (WSNs) have become paramount. As these networks form the backbone of critical data collection and transmission in various sectors, including environmental monitoring, healthcare, and industrial automation, the threat of data tampering looms large, undermining not only the reliability of data but also the safety and efficiency of operations. This paper delves into the burgeoning challenge of data integrity in WSNs, specifically focusing on the vulnerability of these networks to data tampering attacks. The exploration begins with a comprehensive overview of the current landscape of WSNs, highlighting their pivotal role and inherent security weaknesses. It then transitions into a detailed examination of data tampering scenarios, illustrating how these breaches can occur and their potential impact on both the networks and the sectors they serve. The core of this study introduces a novel approach to mitigating these risks: the integration of blockchain technology into WSNs. This integration promises a transformative shift in securing sensor data, leveraging blockchain's inherent characteristics of decentralization, immutability, and transparency. Our proposal outlines a mitigation strategy that encompasses the implementation of a blockchain framework tailored for WSNs. Wireless sensor networks have emerged as a cornerstone technology in a plethora of applications. These networks, characterized by their distributed nature and often operating in unattended environments, are inherently susceptible to various security threats, with data tampering being among the most critical. The initial section of this paper illuminates the escalating threat of data tampering in WSNs. It provides an analysis of recent incidents, underscoring the sophisticated methods employed by attackers and the resulting implications for data integrity and network reliability.

A detailed exploration of the vulnerabilities in current WSN architectures that make them prone to tampering is essential. This part of the paper systematically categorizes these vulnerabilities, ranging from hardware limitations to software loopholes, and examines their role in facilitating data tampering. The impact analysis extends beyond the technical repercussions, considering the socio-economic consequences of compromised data, thereby highlighting the urgency of addressing this issue [21, 22].

The introduction of blockchain as a solution is more than just a technical upgrade; it represents a paradigm shift in how network security is approached in WSNs. This segment delves into the fundamentals of blockchain technology, elucidating how its key features - decentralization, immutability, and consensus mechanisms - align perfectly with the needs of secure, tamper-proof WSNs. The discussion also navigates through the challenges and limitations of integrating blockchain into existing WSN infrastructures, setting a realistic foundation for the proposed solution. Building on the theoretical underpinnings of blockchain technology, the paper then presents a comprehensive mitigation strategy [17, 18, and 20].

This strategy is not just a conceptual framework but a blueprint for practical implementation. It includes architectural models, protocol adaptations, and algorithmic solutions tailored to the unique constraints and requirements of WSNs. The proposed strategy also considers the scalability and energy efficiency aspects, ensuring that the integration of blockchain is viable even in resource-constrained sensor networks which spark a conversation about future directions in network security. The integration of blockchain into WSNs, as proposed, could set a precedent for how emerging technologies can be harnessed to fortify digital infrastructures against evolving cyber threats [23, 24, 25].

This study offers a range of significant contributions to the field. Primarily, it introduces the integration of blockchain technology into wireless sensor networks, significantly boosting their security. We begin by methodically identifying and addressing privacy and security concerns at each layer in Sensor Node applications. This is followed by an in-depth exploration of how Sensor Nodes can be effectively integrated with blockchain technology, assessing its capability to resolve these privacy and security challenges [19].

A key focus of our research is the detailed examination and discussion of the security-enhancing aspects of blockchain technology. By implementing blockchain within wireless sensor networks, we enable data authentication through a decentralized or distributed system, thus enhancing network integrity. The principal contributions of our research are twofold: firstly, introducing blockchain technology as a powerful tool to fortify the security framework of wireless sensor networks, and secondly, ensuring the operational efficiency and reliability of these networks through this innovative technological integration in this paper, we will present the related work (see Table I) in the Section II, Section III will address challenges in privacy protection and security in wireless sensor networks, Section IV presents the methodological model, Section V presents the analysis results and discussion, and a conclusion is present in Section VI.

TABLE I. LIMITATIONS AND PROPOSED SOLUTIONS IN IOT SECURITY, BLOCKCHAIN APPLICATIONS, AND WIRELESS SENSOR NETWORKS RESEARCH

Paper Reference	Title	Research Area	Limitations	Proposed Solutions to Overcome Gaps
[1]	A survey on security and privacy issues in Internet-of-Things	IoT Security and Privacy	Lack of comprehensive security frameworks - Privacy concerns	Developing robust security protocols - Enhancing privacy-preserving mechanisms
[2]	Internet of Things: A survey on the security of IoT frameworks	IoT Security Frameworks	Fragmentation in IoT frameworks - Inadequate security measures	- Standardization of IoT security frameworks - Integration of advanced security measures
[3]	A survey on IoT security: Application areas, security threats, and solution architectures	IoT Security Solutions	Diverse security threats across applications - Complexity in solution architectures	- Tailored security solutions for specific applications - Simplification of security architectures
[4]	Genetic algorithm-based optimized leach protocol for energy efficient wireless sensor networks	WSN Energy Efficiency	Energy consumption in WSNs - Inefficient data transmission protocols	- Use of genetic algorithms for protocol optimization - Development of energy-efficient protocols
[5]	Blockchain based secure data handover scheme in non-orthogonal multiple access	Blockchain in Telecommunications	Security vulnerabilities in data handover - Inefficiency in access methods	Blockchain for secure data management - Optimization of access methods
[6]	Blockchain-enabled spectrum access in cognitive radio networks	Blockchain in Cognitive Radio Networks	Spectrum access inefficiencies - Security issues in spectrum management	Blockchain for decentralized spectrum access - Enhanced security protocols
[7]	Data sharing and tracing scheme based on blockchain	Blockchain for Data Management	Lack of transparency in data sharing - Inefficient tracing mechanisms	Blockchain for improved transparency and efficiency - Advanced tracing schemes
[8]	A consensus and incentive program for charging piles based on consortium blockchain	Blockchain in Energy Systems	Inefficient management of charging infrastructure - Lack of consensus mechanisms	Consortium blockchain for management and consensus - Incentive programs for participation
[9]	Data collection for security measurement in wireless sensor networks	WSN Security	Challenges in secure data collection - Inadequate security measurement techniques	Improved data collection methods - Enhanced security measurement methodologies
[10]	Security attacks and countermeasures in surveillance wireless sensor networks	WSN Security in Surveillance	Prevalence of security attacks - Ineffectiveness of current countermeasures	Development of robust security countermeasures - Research on attack prevention strategies

II. RELATED WORK

The most prevalent model in today's network software applications is the centralized system. This model exercises direct control over each unit and handles signal processing at each centralized hub. In this setup, the management of rights by the central entity is entirely dependent on individual nodes, with the entire network infrastructure operating to receive and transmit data based on these rights. In contrast, a distributed network system is exemplified by the peer-to-peer (P2P) model. P2P networks, used extensively in online file sharing and live streaming services, include applications like Torrent file downloading.

Blockchain technology, following the footsteps of BitTorrent, also operates on a peer-to-peer network protocol. In this network, all nodes are of equal status, functioning independently of a centralized control system or an intermediary for transactions. Nodes have the flexibility to join or leave the network at any time and can simultaneously offer and utilize services. Each node in this network acts both as a server and a client. The overall strength of the system, in terms of processing capability, data security, and resilience to damage, grows with the number of nodes. Bitcoin, a well-known application of this technology, also operates on the P2P protocol. Unlike traditional financial systems where trusted central institutions act as intermediaries, Bitcoin's operations are direct between users, facilitated by the peer-to-peer network protocol, as referenced in [5, 6].

A comprehensive blockchain system encompasses various components: data blocks for storing information, cryptographic signatures, system logs, a peer-to-peer network infrastructure, methodologies for system maintenance, computational tasks for data mining, rules for proof-of-work, mechanisms for transmitting anonymous data, “Unspent Transaction Output” (UTXO) models, Merkle trees, among other technical aspects. Leveraging these technological advancements, blockchain creates a continuous, decentralized network powerhouse, facilitating services like transmission, verification, and record-keeping, as detailed in study [7].

This approach allows for the creation of a sensor data record derived from the transaction history of a blockchain. In a typical blockchain network, a new block is generated approximately every ten minutes, consisting of a header and a body. The header of each block includes several key elements: the current block number, the starting block's hash value, a timestamp, a random number (nonce), the hash value of the current block, and a Merkle tree. The body of the block is primarily where the sensor data are located. Each sensor data entry is securely stored in the block of the research system’s record, readily accessible to authorized users. The Merkle tree within the block ensures the integrity of each piece of sensor data by digitally signing it, thereby preventing duplication. Upon gathering all sensor data, the system utilizes the Merkle-tree hash method to generate "Merkle-root" values, which are then included in the block’s description section [8].

Reference in [9] presents data security protocols specifically tailored for wireless sensor net-work environments. Further examination of security threats and their mitigation in wire-less sensor networks, particularly those used in monitoring applications, was suggested in [10]. In study [11], the application of sensor fusion in wireless sensor networks is explored for the purpose of detecting mobile intruders in surveillance scenarios. Reference in [12] introduces a fusion-based system for remote sensing applications, leveraging wireless interactive media sensing devices.

One of the most appealing aspects of blockchain technology is the level of privacy it offers. However, this can sometimes result in transparency issues. The system self-audits, frequently reviewing the digitized value ecosystems that handle transactions, typically every ten minutes. This process ensures transparency and the absence of corruption. In a block-chain, associating a specific user with a public address set is challenging, as the user’s identity is shielded behind a complex encryption [13]. Various security-related studies in different domains are mentioned below with corresponding references.

Research in [14] addresses the development of a blockchain network for cross-domain image sharing. This network employs a consensus blockchain to facilitate the sharing of medical and radiological images among patients. The author emphasizes consensus among select trustworthy institutions to maintain a robust consensus mechanism, simplifying the management of advanced security and privacy modules.

According to research in [15], the application of blockchain technology has significantly improved the transfer of medical records in Health 4.0 applications. This includes enhanced compatibility of healthcare databases, easier access to clinical documentation, prescription databases, and effective tracking of medical devices. Additionally, the authors propose an access control policy designed to optimize the sharing of medical information across various healthcare providers.

Several studies have advocated for the implementation of an ad hoc on-demand distance vector (AODV), a robust routing protocol that leverages prior encoding to counteract

III. Privacy and Security Challenges in Wireless Sensor Networks

With the evolution of sensor node technology, applications based on sensor nodes have begun to replace traditional ones. Significant efforts have been invested in developing the architecture and protocols for sensor node-based products. However, as highlighted in study [1], privacy and security issues within sensor node systems remain a primary concern. These systems face inherent limitations and are susceptible to a range of security threats, which have been systematically categorized in a layer-wise manner for sensor node-based applications.

The structure of sensor node applications, as discussed in [2], involves multiple frame-works for building these applications, each presenting its own set of security and privacy challenges. Eight potential frameworks have been identified, emphasizing the unique concerns in each for securing and maintaining privacy. As noted in references [3, 4], security and privacy issues, particularly in the realms of authentication and data protection, are among the most daunting challenges in the design of sensor node applications. The authors suggest innovative solutions, including the use of blockchain, cloud computing, and advanced device analytics, as potential methods to address these challenges. The sensor node infrastructure is broadly divided into three layers: physical, network, and application.

Each layer presents distinct security vulnerabilities that need to be addressed to ensure the overall integrity and confidentiality of the sensor node ecosystem [16].

Wireless Sensor Networks (WSNs) are fundamental in numerous applications, ranging from environmental monitoring to smart city infrastructures. However, their open and distributed nature introduces significant privacy and security challenges that must be ad-dressed to ensure their effective and safe operation.

1) Vulnerability to external attacks: WSNs are often deployed in unsecured environments, making them susceptible to various forms of cyber-attacks. These include eavesdropping, where attackers intercept sensitive information, and more sophisticated attacks like node capture and physical tampering, where the attacker gains control of a sensor node.

2) Data integrity and authentication issues: Ensuring the integrity and authenticity of the data collected and transmitted by sensor nodes is crucial. Any tampering with data can lead to incorrect decision-making, with potentially catastrophic consequences, especially in critical applications like healthcare monitoring systems.

3) Privacy concerns: Sensor nodes often collect sensitive information. Protecting the privacy of this data against unauthorized access and ensuring compliance with data protection regulations pose significant challenges.

4) Network security weaknesses: Due to resource constraints in WSNs (like limited battery life and computational power), implementing robust encryption and other traditional security measures can be challenging. This limitation makes WSNs more vulnerable to security breaches compared to more resource-rich networks.

5) Internal threats and insider attacks: WSNs are not only vulnerable to external threats but also to internal ones. Compromised or malfunctioning nodes within the network can lead to the dissemination of false data, disrupting network operations.

6) Scalability and dynamic network topology: The scalable nature of WSNs and their dynamic topology, with nodes frequently joining and leaving, complicate the implementation of comprehensive security protocols that can adapt to changing network configurations.

7) Resource constraints and energy efficiency: One of the defining features of WSNs is their limited resources in terms of energy, memory, and computational power. Security mechanisms, which often require substantial computational resources, must be designed to be energy-efficient to prolong the lifespan of the sensor nodes. Striking a balance between security and energy efficiency is a critical challenge [17].

8) Secure data aggregation: In WSNs, raw data collected by individual sensor nodes are of-ten aggregated to reduce communication overhead and save energy. Ensuring the security and integrity of this aggregated data is crucial, as tampering or false data injection at this stage can have wide-ranging implications.

9) Key management and distribution: Secure communication in WSNs typically relies on cryptographic methods, which in turn depend on effective key management strategies. However, the dynamic nature of WSNs, combined with resource constraints, makes key distribution, management, and revocation a complex task.

10) Physical layer security: Given the likelihood of sensor nodes being deployed in physically unsecured locations, they are prone to capture and tampering. Protecting the physical layer of WSNs and developing tamper-resistant hardware are important aspects of ensuring overall network security.

11) Cross-layer security solutions: Traditional network security solutions focus on specific layers of the network. However, in WSNs, a cross-layer design approach — where security solutions are integrated across different layers of the network protocol stack — can offer more robust protection.

12) Trust and reputation systems: Implementing trust and reputation systems within WSNs can help in identifying and isolating malicious or compromised nodes. These systems, however, must be lightweight and scalable to suit the network's constraints.

13) Legal and regulatory compliance: Adhering to evolving legal and regulatory standards for data protection and privacy, especially when WSNs are used in sensitive applications, adds another layer of complexity. Ensuring compliance while maintaining operational efficiency is a significant challenge.

14) User awareness and training: The human factor plays a crucial role in the security of WSNs. Training users and administrators to understand potential security threats and to follow best practices is essential for maintaining network integrity.

The impact of privacy issues on the performance of Wireless Sensor Networks (WSNs) is a multifaceted concern. Privacy challenges can affect WSNs in several ways, often leading to compromises in their efficiency, effectiveness, and overall functionality.

15) Increased overhead and reduced efficiency: To address privacy concerns, additional layers of data protection and encryption may be required. While these are crucial for safe-guarding sensitive information, they also introduce extra computational and communication overhead. This increased load can strain the limited resources of sensor nodes, lea-ding to reduced network efficiency and shorter node lifespans due to faster battery depletion. Implementing privacy-preserving mechanisms often involves complex algorithms and processing, which can result in latency. In real-time applications or scenarios where timely data transmission is critical (such as in emergency response systems), this delay can impair the overall performance of the WSN. Ensuring privacy in WSNs becomes increasingly challenging as the network scales. The larger the network, the more data is transmitted, and the more nodes are involved, increasing the risk of privacy breaches. Maintaining strong privacy protocols in a scalable manner without impacting network performance is a significant challenge. In some cases, to protect privacy, data may be anonymized or aggregated before being transmitted. While this is effective for privacy preservation, it can sometimes lead to a loss of data granularity or specificity, thereby reducing the utility or accuracy of the data for certain applications. WSNs often need to balance resource allocation between primary functions (like data collection and transmission) and privacy-preserving functions. This can lead to sub-optimal resource allocation, where either privacy or primary functionality is compromised. Privacy breaches can undermine the trust in a WSN's reliability.

If end-users or administrators believe that their data is not being handled securely, it can lead to reduced adoption and trust in these networks, thereby impacting their broader application and effectiveness. Addressing privacy issues requires careful planning and de-sign, which can increase the complexity of WSN systems. This might lead to more challenging implementation and maintenance, requiring more skilled personnel and resources, thereby impacting the cost-effectiveness and practical deployment of WSNs. Adhering to privacy regulations and standards can impose additional constraints on the design and operation of WSNs. Navigating these legal requirements can be complex and might limit how WSNs are deployed and used, potentially impacting their performance in certain scenarios.

IV. Proposed Model

Designing a model based on blockchain technology to enhance security monitoring in Wireless Sensor Networks (WSNs) involves addressing (see Fig. 1) several key aspects: the unique characteristics and constraints of WSNs, the principles of blockchain technology, and the integration of these two to improve security.

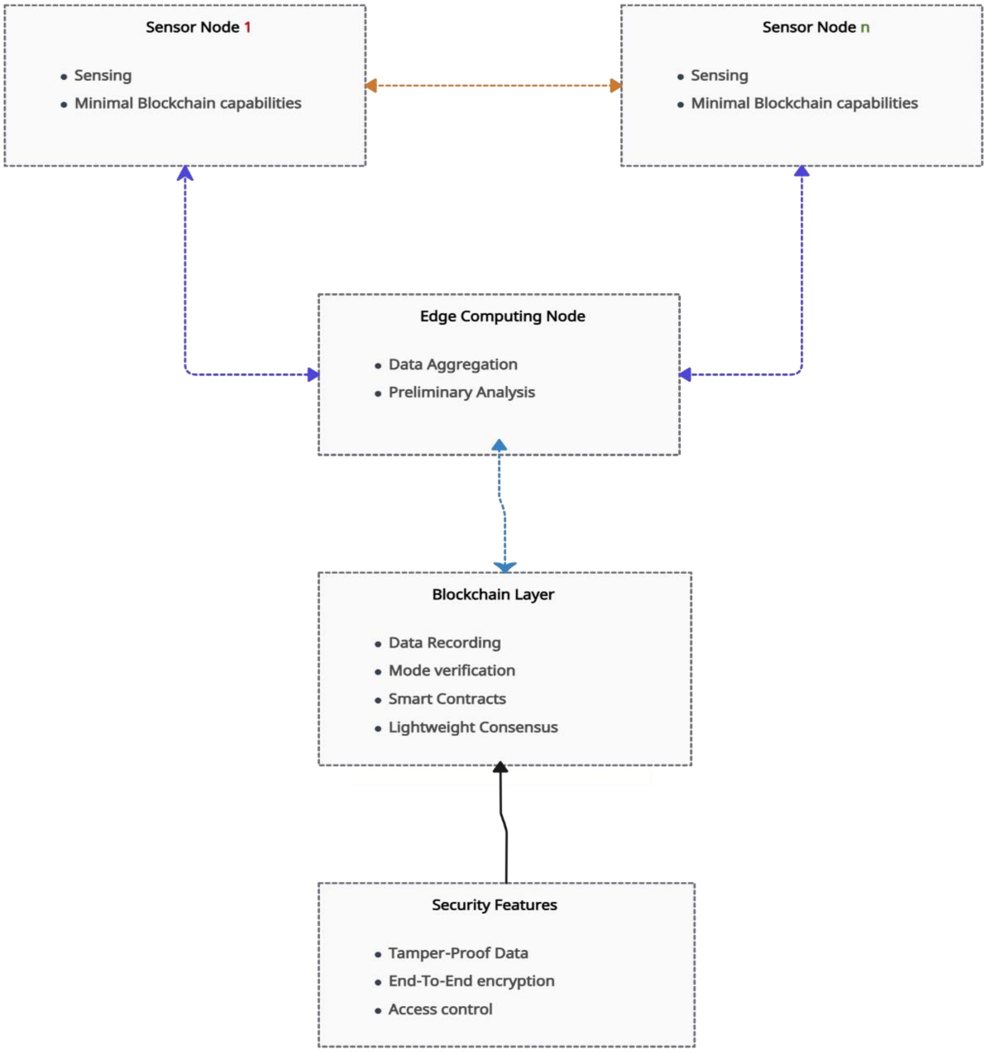

Fig. 1. Proposed model.

Here's a conceptual outline for our proposal model:

A. Architecture

1) Blockchain layer: This involves integrating a lightweight blockchain with the Wireless Sensor Network (WSN). The blockchain layer serves as the backbone for secure data management, ensuring data integrity and facilitating secure communications between nodes. Given the resource constraints in WSNs, the blockchain technology used must be lightweight enough to not overburden the network.

2) Sensor nodes: These are the basic units of WSNs and in this model, they are equipped with minimal blockchain capabilities. This means each sensor node can participate in the blockchain network, contributing to data recording and verification processes, while still performing their primary function of sensing and data collection.

3) Edge computing: To alleviate the computational load on sensor nodes, edge computing is employed. It involves processing data at the edge of the network, closer to where it's being generated. This approach handles computation-intensive tasks, like data aggregation and preliminary analysis, reducing the latency and conserving the energy of sensor nodes.

B. Integration

1) Data recording: Sensor data is recorded on the blockchain, ensuring its integrity and immutability. This aspect is crucial for maintaining the trustworthiness of the data collected by various sensors.

2) Node verification: Blockchain technology is utilized to authenticate sensor nodes. This is essential to prevent malicious or compromised nodes from entering and affecting the network.

3) Smart contracts for automated responses: These are self-executing contracts with the terms of the agreement between nodes written into code. They are used to trigger actions automatically based on sensor data, enhancing the network's responsiveness and automation.

C. Energy Efficiency

1) Lightweight consensus mechanism: Since traditional blockchain consensus mechanisms (like Proof of Work) are energy-intensive, a less energy-consuming mechanism, such as Proof of Authority or a custom lightweight algorithm, is proposed. This mechanism ensures network security and integrity without draining sensor node resources.

2) Data aggregation: Before recording data on the blockchain, it's aggregated at edge computing nodes. This reduces the volume of data that needs to be processed and stored on the blockchain, conserving energy and bandwidth.

D. Security Features

1) Tamper-proof data: Blockchain's immutable ledger ensures that once data is recorded, it cannot be altered, enhancing the security and reliability of the data.

2) End-to-end encryption: Secure communication channels are established between sensor nodes, protecting the data from interception or tampering during transmission.

3) Access control: Smart contracts are employed to manage access to the data, ensuring that only authorized entities can access or modify it.

E. Challenges and Considerations

1) Scalability: As the WSN grows, managing an increasing number of sensor nodes becomes a challenge. The system must be designed to efficiently scale, maintaining performance and security.

2) Interoperability: The system should be capable of working with different types of sensors and networks, ensuring flexibility and adaptability.

3) Resource management: Balancing the resource demands of blockchain (like storage and computational power) with the limited resources available on sensor nodes is critical. Efficient resource management strategies are required to maintain network performance and longevity.

F. Key Elements in the Diagram:

1) Sensor nodes: Represents individual sensors in the WSN with minimal blockchain capabilities for participating in network security functions.

2) Edge computing node: A node that handles data aggregation and preliminary analysis to reduce the load on individual sensor nodes.

3) Blockchain layer: The core of the model, handling data recording, node verification, smart contract execution, and maintaining the consensus mechanism.

4) Security features: Ensuring the integrity and confidentiality of the data through tamper-proof records, encryption, and access control.

G. Simulation Parameters

Before detailing the simulation scenario we have explored in this work, let's look at how data manipulation using the Internet Control Message Protocol (ICMP) involves an adversary exploiting the protocol's functions to alter or interfere with the transmission of data across a network. ICMP, commonly used for sending error messages or operational information in networks (like ping commands to check on the availability of a host), can be an attack vector for malicious entities.

1) Here's how it can be utilized for data manipulation: ICMP Redirection Attacks: Attackers can use ICMP redirect packets to manipulate the routing table of a host. By sending a crafted ICMP redirect message, an adversary can convince a host to route its traffic through an attacker-controlled machine, allowing for the interception and potential alteration of data. ICMP Tunneling: This technique involves encapsulating data within ICMP echo request and response messages. An attacker could leverage this method to bypass security measures like firewalls that may not inspect ICMP packets as rigorously as other protocol traffic, allowing data to be covertly manipulated and extracted from a network.

2) ICMP flood attack: While not a direct method of data manipulation, an ICMP flood attack can overwhelm a target with a barrage of ICMP packets, potentially causing legitimate responses to be lost or delayed. This can indirectly affect data integrity if systems are relying on timely ICMP responses for operations.

3) ICMP payload manipulation: An adversary might alter the data carried within an ICMP packet's payload. Since ICMP can transmit error messages and other network operational data, manipulating this information can lead to misconfigured network devices or misinformed network administrators.

Creating a scenario for an ICMP (Internet Control Message Protocol) attack with data manipulation involving 200 nodes over the course of an hour would involve several steps and considerations. Define a network topology with 200 nodes. These could be servers, IoT devices, computers, etc., connected in a specific arrangement (e.g., star, mesh, or a custom topology). An ICMP flood attack would be simulated, where one or more nodes (the attackers) would overwhelm the network by sending an excessive number of ping requests to one or multiple target nodes. The attack would last for one hour.

During the attack, the network's throughput and energy consumption of each node would be monitored. Measured in bits per second (bps) or packets per second (pps), you'd record the successful transmission rates of data across the network. This data would likely decrease as the ICMP attack impacts the network's performance. Each node's power usage would be monitored; typically increasing due to the processing of the excessive ICMP re-quests.

4) Simulation tools: To simulate this scenario, we use network simulation tools like NS3, OMNeT++ and Mininet for a more controlled environment. These tools allow to model the network, simulate the traffic and attacks, and collect the necessary data.

We will use a Python script to generate throughput and energy consumption data for 200 nodes over the course of an hour (see Fig. 2). In the following section we will discuss and analyze the results of the simulation and demonstrate the role of blockchain in the security of WSNs.

```
import numpy as np
import pandas as pd
# Constants
NODES = 200
DURATION_HOURS = 1

# Assume a normal distribution for throughput (in bps) and energy
consumption (in Joules)

throughput_mean = 10000  # average throughput
throughput_std = 2000    # standard deviation of throughput
energy_mean = 50         # average energy consumption
energy_std = 10          # standard deviation of energy consumption

# Randomly generate throughput and energy consumption data for
200 nodes
np.random.seed(0)  # Seed for reproducibility
throughput_data = np.random.normal(throughput_mean,
throughput_std, NODES)
energy_data = np.random.normal(energy_mean, energy_std,
NODES)

# Ensure that throughput and energy consumption are not negative

throughput_data = np.clip(throughput_data, 0, None)
energy_data = np.clip(energy_data, 0, None)
# Create a DataFrame to represent the array structure
data_array = pd.DataFrame({
    'node_id': range(1, NODES + 1),
    'throughput': throughput_data,
    'energy_consumption': energy_data
})

# Save the complete DataFrame to a CSV file

csv_file_path = '/mnt/data/simulated_icmp_attack_data.csv'
data_array.to_csv(csv_file_path, index=False)

print(csv_file_path)
```

Fig. 2. Python script attack simulation.

V. Results Analysis

The result depicted in the two graphs illustrates the outcomes of a simulated ICMP attack on a network of 200 nodes, focusing on throughput and energy consumption.

The energy consumption graph (see Fig. 3) reveals a relatively uniform distribution across the nodes, with most nodes exhibiting energy consumption around the mean value, though there are some variations. This indicates that the energy usage during the ICMP attack was fairly consistent across the network, with no significant outliers. This could suggest that all nodes were similarly engaged in responding to the ICMP requests, thereby consuming energy at comparable rates.

To formulate mathematical equation for generating energy consumption data, as seen in the simulated ICMP attack scenario.

$$\text{Energy Consumption } (t) = P\text{base} + P\text{attack}(t) \tag{1}$$

Where: Pbase is the base power consumption of the node in a normal state.

Pattack(t) is the additional power consumption due to the attack at time t, which could be a function of the intensity of the attack and the effort involved in running the block-chain-based mitigation. Example Functions Network Efficiency Function E(t) Could be a constant representing average efficiency, say 0.9 (90% efficiency). Alternatively, a more dynamic model could involve a time-varying function, possibly sinusoidal to simulate daily variations. Attack Impact Function A(t): A step function that increases sharply when the attack begins and decreases as mitigation strategies take effect. For a more nuanced model, this could be a sigmoid function to represent a gradual increase and decrease in attack intensity. Additional Power Consumption Function attack Pattack(t): A function that increases from zero to a certain level when the attack starts, reflecting the extra workload. This could also be modeled as a step function or a gradual increase if mitigation strategies ramp up over time.

The throughput graph depicted in Fig. 4, on the other hand, displays a more varied pattern. The throughput for each node varies significantly, with some nodes maintaining high throughput rates while others drop lower. This variation could be a result of the network's attempt to manage the excessive traffic from the ICMP flood. Some nodes may have been more successful in mitigating the attack and thus maintained higher throughput, while others were more adversely affected, resulting in reduced throughput. The peaks and troughs in the throughput graph could also reflect the dynamic nature of network traffic under stress conditions, where certain nodes might be temporarily able to handle the traffic before being overwhelmed.

To formulate mathematical equation for generating throughput, as seen in the simulated ICMP attack scenario, we'll define equations based on typical models used in networking and energy consumption simulations.

$$\text{Throughput } (t) = C \times E\ (t) \times (1 - A\ (t)) \tag{2}$$

Where: C is the maximum network capacity (in bps). E(t) is the network efficiency at time t, ranging from 0 to 1. A(t) is the impact of the attack at time t, ranging from 0 (no impact) to 1 (complete disruption). The network efficiency E(t) could be a function that ac-counts for normal network variability, and A(t) could be a function representing the intensity of the attack over time.

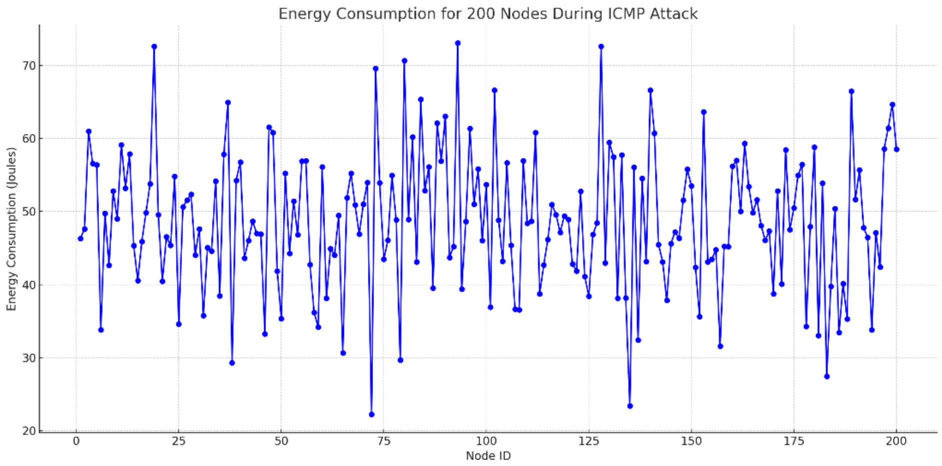

Fig. 3. Energy consumption graph during ICMP attack.

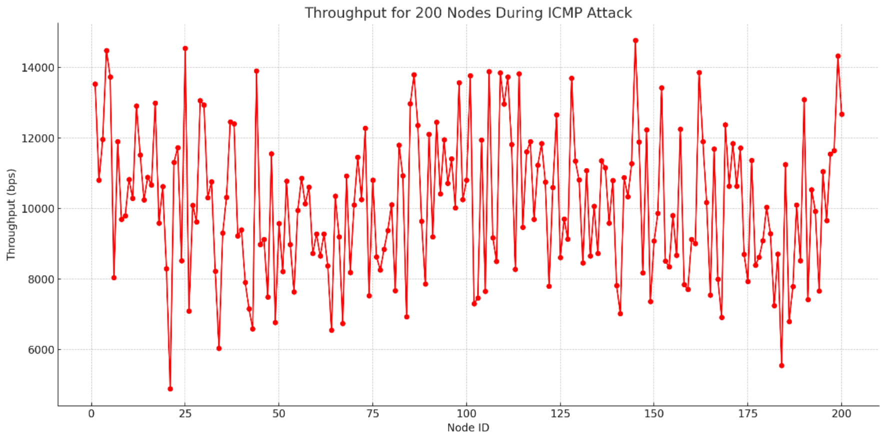

Fig. 4. Throughput graph during ICMP attack.

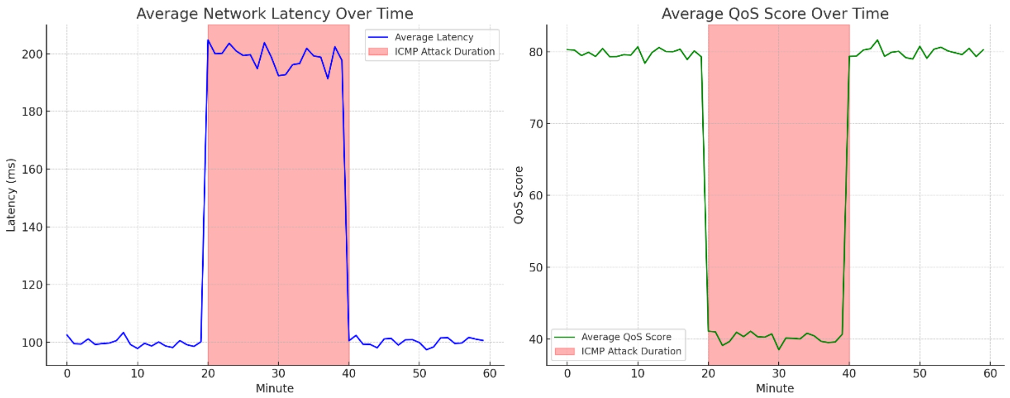

Fig. 5. Latency and lower QoS scores during ICMP attack.

During the ICMP attack (minutes 20 to 40), the nodes experience higher latency and lower QoS scores (see Fig. 5). Outside of the attack period, the nodes have normal latency and QoS levels.

1) Average network latency over time: This graph shows the average latency across all nodes for each minute of the hour. The red shaded area indicates the duration of the ICMP attack (minutes 20 to 40). You can observe a significant increase in latency during the attack period.

2) Average QoS score over time: This graph illustrates the average Quality of Service (QoS) score across all nodes per minute. Similar to the latency graph, the red shaded area marks the ICMP attack duration. The QoS score noticeably drops during the attack, indicating a degradation in network performance.

Designing a blockchain-based model to detect and mitigate ICMP attacks requires leveraging the inherent characteristics of blockchain technology, its distributed nature, immutability, and consensus mechanisms. Below is a high-level design of such a model: Block-chain Model for ICMP Attack Detection and Mitigation. Network Configuration, each node in the network operates as a blockchain peer. The blockchain network uses a consensus protocol that is suitable for the network's scale and transaction throughput needs, such as Proof of Work (PoW), Proof of Stake (PoS), or a Byzantine Fault Tolerant (BFT) consensus mechanism.

Decentralized Consensus for Attack Detection, when a node detects anomalous behavior, it proposes a block that flags the potential attack. Other nodes validate the block by executing the smart contract against their copy of the transaction data. If the consensus is reached that an anomaly exists, the network collectively identifies it as an ICMP attack.

Mitigation Protocol, upon detecting an attack, the smart contract triggers a mitigation protocol. This protocol could involve rate-limiting, automatically blocking traffic from suspicious sources, Transaction and Block Structure, network requests and traffic data are en-capsulated in blockchain transactions. Each transaction includes metadata such as timestamp, source, destination, and packet size. Blocks contain multiple transactions and are linked to previous blocks, creating a tamper-evident chain. Anomaly Detection Smart Contract Deploy a smart contract on the blockchain that defines the rules for normal net-work behavior. The smart contract contains the logic to analyze transactions for signs of an ICMP attack, such as excessive traffic from a single source or high traffic volumes to a specific node. Nodes automatically execute this contract as they process transactions, enabling real-time monitoring or redistributing network load. Mitigation actions are also recorded on the blockchain for accountability and traceability. Continuous Learning, the smart contract can be updated based on the attack patterns observed, which can be done through a governance mechanism allowing node operators to vote on updates. Machine learning algorithms could be integrated to adaptively recognize new types of ICMP attack patterns. Simulation and Testing before deploying simulate the blockchain model in a controlled environment using the previously obtained ICMP attack data. Adjust the model parameters based on the simulation results to optimize detection accuracy and mitigation effectiveness.

Implementation Considerations, Scalability the blockchain must handle a large volume of transactions without significant latency, which is critical for real-time attack detection and mitigation. Privacy, Transaction data should be anonymized to prevent leakage of sensitive network information.

Resource Usage, Blockchain and smart contract operations consume computational re-sources, which must be balanced against the energy consumption of the nodes.

By utilizing a blockchain-based approach, you can create a distributed system that is resistant to tampering and centralized failure points. The model's effectiveness will depend on its proper configuration, smart contract logic, and the network's ability to reach consensus quickly to respond to detected threats.

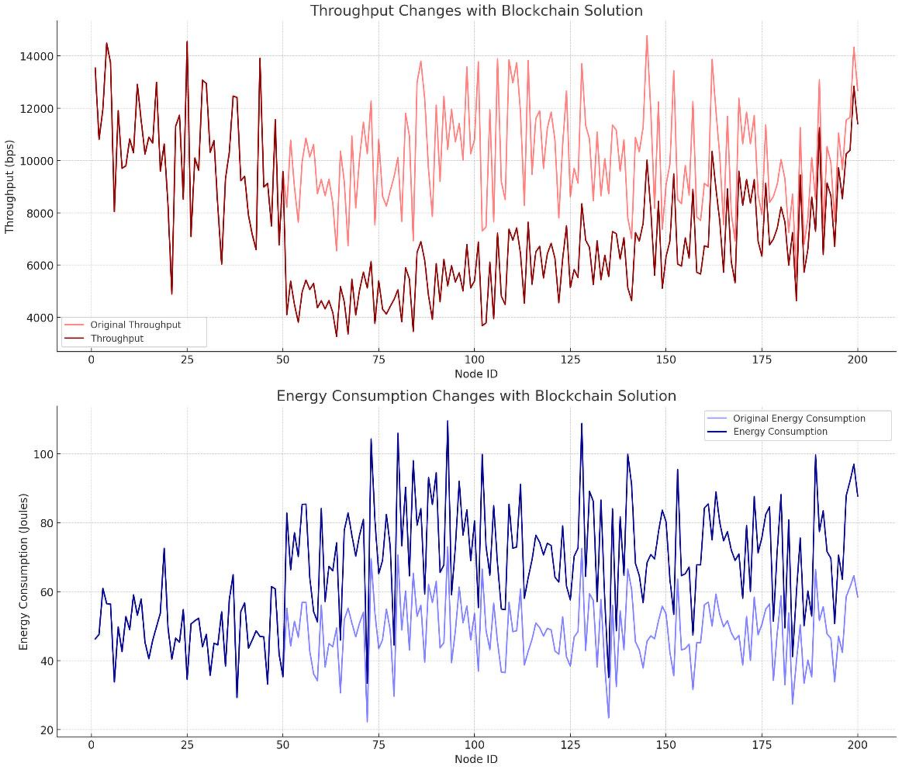

Fig. 6. Expected impact of a Blockchain solution on network performance during and after an ICMP attack.

Fig. 6 present changes in throughput and energy consumption for the 200 nodes in the network, following the implementation of a blockchain solution to detect and mitigate ICMP attacks.

3) Throughput graph (Top): The 'Original Throughput' (in red) shows the throughput before implementing the blockchain solution. The 'Throughput' (in dark red) indicates the expected changes after the blockchain solution is in place. There is a significant drop in throughput around node 50, representing the onset of the ICMP attack. Post node 100, where the mitigation starts to take effect, the throughput gradually recovers, although it does not fully return to the original levels.

4) Energy consumption graph (Bottom): The 'Original Energy Consumption' (in blue) represents energy consumption before the blockchain solution. The 'Energy Consumption' (in dark blue) shows an increase in energy consumption beginning at node 50, coinciding with the start of the attack and the increased processing demands of the blockchain-based mitigation strategies. The energy consumption remains elevated compared to the original levels, reflecting the continuous operation of the blockchain mechanisms.

To incorporate a blockchain solution into this simulation and analyze its impact on latency and QoS (Quality of Service), we need to consider how blockchain technology could influence these metrics (see Fig. 7). Typically, blockchain can enhance security and integrity in network communication, but it might also introduce additional latency due to the time taken for consensus protocols and data verification.

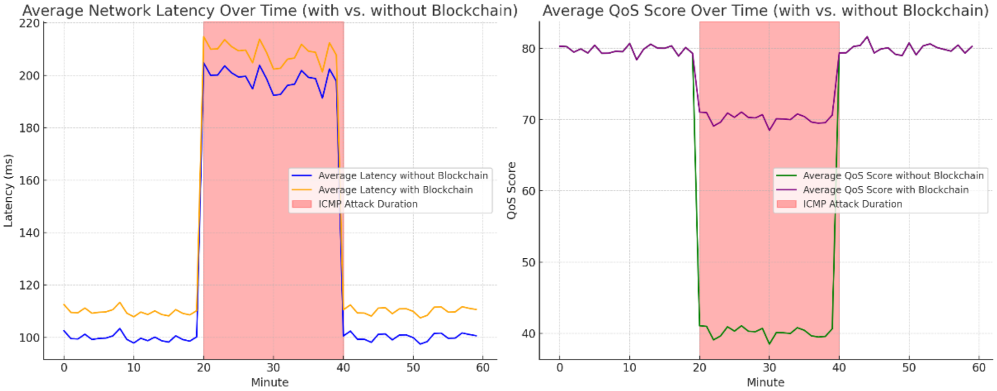

Fig. 7. Network performance with and without a blockchain solution.

Before Blockchain Implementation:

The network behaves as in the previous simulation, with increased latency and decreased QoS during the ICMP attack.

After Blockchain Implementation:

Security Improvement: The blockchain solution significantly mitigates the impact of the ICMP attack, reducing its effect on QoS. Latency Increase: However, due to the overhead of blockchain operations (like consensus mechanisms), there is a slight increase in baseline latency across the network, even outside of attack conditions.

VI. Conclusion

In conclusion, Wireless Sensor Networks (WSNs) are crucial in various applications, ranging from environmental monitoring to industrial automation and healthcare. However, their open and distributed nature makes them susceptible to various cyber-attacks, notably data manipulation and Denial of Service (DoS) attacks like ICMP flooding. These attacks can significantly impair the network's functionality, compromising the integrity and availability of the data. Data manipulation attacks can alter or fabricate sensor data, leading to incorrect decisions or actions based on this compromised data. In our simulation, an ICMP flood attack caused significant spikes in network latency and a notable degradation in Quality of Service (QoS). Blockchain technology, with its inherent characteristics of decentralization, transparency, and immutability, offers a compelling solution to enhance the security of WSNs. By integrating blockchain, each data transaction or sensor reading can be verified and recorded in a tamper-resistant manner. In the simulated scenario, network experienced high latency and low QoS during the ICMP attack, indicating vulnerability to such attacks. There was an overall increase in baseline latency due to blockchain's computational overhead. However, during the ICMP attack, the block-chain-enabled network showed a smaller increase in latency and a significantly lesser decrease in QoS. This resilience can be attributed to the blockchain's ability to maintain data integrity and network operation even under attack conditions. About Mitigation Strategy, Implementing a lightweight blockchain protocol, optimized for WSNs, to ensure data integrity and resilience against manipulation attacks. Hybrid Security Approach combines traditional security measures (like firewalls and intrusion detection systems) with block-chain to provide a layered defense mechanism. Optimization for Latency develops and integrates blockchain protocols specifically optimized for low latency to mitigate the in-creased baseline latency introduced by blockchain. Dynamic Adaptation implement a system that dynamically adjusts blockchain's security level based on real-time threat analysis, balancing between optimal performance and security. Continuous Monitoring and Updating regularly monitor network performance and security, updating the block-chain protocol as needed to address new vulnerabilities and maintain efficiency. Energy Efficiency Considerations given the limited energy resources in WSNs, tailor the block-chain solution to be energy-efficient, possibly through consensus mechanisms that require less computational power.

Integrating blockchain into WSNs presents a promising approach to enhance security against data manipulation attacks. While it introduces challenges like increased latency and demands on energy, these can be mitigated through careful design and optimization. The proposed strategy aims to leverage the strengths of blockchain while addressing its limitations, ensuring robust, secure, and efficient operation of Wireless Sensor Networks.

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Web-based Expert Bots System in Identifying Complementary Personality Traits and Recommending Optimal Team Composition

Web-based Expert Bots System for Optimal Team Composition

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Abstract*—The use of web-based expert systems in the workplace has become increasingly common in recent years, with companies using these automated tools to streamline a range of tasks, from customer service to employee training. However, the potential of web-based expert bots systems to help build more effective teams by identifying employees with complementary personality traits and providing recommendations for team composition has received less attention. This paper investigates the application of a web-based expert bots' system in identifying complementary personality traits among employees to recommend optimal team compositions. We developed a web-based expert bot system, augmented by a chatbot interface, to evaluate and synthesize employee personality profiles for improved team alignment. The results, derived from questionnaire feedback and prototype assessments, demonstrate the system's capability to enhance team performance metrics and behavioral competencies. The discussion outlines the system's advantages, and its potential in organizational settings, and acknowledges its limitations. Web-based expert systems with chatbots that exhibit unique personalities tend to be more engaging and effective. Consequently, this system is expected to not only foster better team cohesion but also to increase user involvement and satisfaction. Future work is dedicated to expanding the system's capabilities and conducting extensive field testing to establish its practical effectiveness.

***Keywords*—Web-based expert system; personality traits; team composition; workplace efficiency and chatbot integration**

I. Introduction

Team composition is a multifaceted challenge, requiring a delicate balance of skill sets, personality traits, and roles [1]. This complexity is further underscored by the influence of individual differences, such as personality traits, values, and demographics, on team dynamics and performance [2]. In the context of software engineering project courses, team composition is particularly challenging due to the need to consider practical constraints, skill distribution, and project motivation [3]. The difficulty lies not only in identifying these characteristics but also in predicting the dynamic interplay between them, which can significantly impact team cohesion, adaptability, and ultimately, the success of the team's objectives. Effective team composition requires a nuanced approach that takes into account the individual and collective needs of the team and the goals of the project.

The evolution of web-based expert systems in organizational settings has been marked by significant advancements in artificial intelligence and machine learning. Initially, these systems focused on automating simple tasks and evolved to perform complex functions like data analysis and decision support. Currently, they are integral in streamlining operations, enhancing decision-making, and providing predictive insights across various business functions. Their ability to process vast amounts of data with sophisticated algorithms allows for unprecedented accuracy in tasks such as market analysis, customer service, and strategic planning, making them indispensable in modern organizational infrastructure.

Research on the significance of expert systems in human resources, particularly in identifying and harnessing complementary personality traits for team composition, has yielded valuable insights. Radović et al. [4] found that a combination of extraversion and openness to experience is crucial for team performance, while Gilal et al. [5]identified extroversion as a dominant personality type for effective software team roles. It has been emphasized the importance of emotional stability, agreeableness, and a predisposition to be a team player in predicting task performance and cohesion [6]. These findings underscore the potential of expert systems in optimizing team composition by considering these key personality traits.

Moreover, the use of chatbots in team optimization has been explored in various studies. It has been highlighted the potential of chatbots to enhance team performance [7], [8]. Bansal et al. [9] takes this a step further by proposing the optimization of AI systems for teamwork, emphasizing the need for human-centered design. Tennent et al. [10] introduces the concept of a peripheral robotic object, Micbot, which has been shown to improve group engagement and problem-solving performance. These studies collectively underscore the potential of chatbots and AI systems in team optimization, particularly in the areas of emotion management, and productivity in workplace environments.

The primary aim of this study is to explore the efficacy of web-based expert bots systems in enhancing team effectiveness within organizations. This inquiry is driven by the central research question: How can web-based expert bots systems help employers build more effective teams by identifying employees with complementary personality traits, team performance, team behavioral competencies and providing recommendations for team composition? To achieve this aim, the study is guided by several key objectives: Firstly, to create a robust knowledge base that informs team composition, derived from three distinct assessment methods. Secondly, to develop an interactive chatbot tailored for individual employer assessments. Finally, to construct a prototype web-based expert bot system capable of accurately identifying crucial factors such as personality traits, team performance metrics, and team behavioral competencies. Through these objectives, the study seeks to contribute significantly to the field of organizational psychology and team dynamics, leveraging advanced technology to foster more efficient, cohesive, and productive workplace environments.

The subsequent section provides an overview of team composition strategies. It is followed by a methodology section that outlines the framework of the integrated system, comprising a rule-based chatbot for personality analysis and a comprehensive web-based expert system equipped with team management and assessment tools. Results from questionnaires and prototype evaluations are presented next. The discussion emphasizes the system's benefits and acknowledges its limitations. The paper concludes by reflecting on the findings and suggesting directions for future research.

II. Background

Building productive teams is vital for organizations looking to maximize productivity and innovation in the dynamic, collaborative work environments of today. The personality alignment of team members is a crucial factor to consider because it affects team performance. Team dynamics, creativity, and problem-solving skills have all been shown to improve when team members have complementary personality traits. Radović et al. [4] stated that a team's performance may be influenced by a combination of personality qualities. While there has been much research on how team dynamics and members' personality traits affect team performance,

A team employee refers to an individual who is part of a team within an organization and works collaboratively with other team members to achieve shared goals and objectives. Unlike individual contributors who work independently, team employees actively engage in group dynamics, contribute their skills and expertise, and collaborate with others to accomplish tasks and projects. The term "team composition" describes the composition or structure of a team, including the traits, competencies, and roles of each member. It entails carefully selecting and assigning people in order to create a strong team that can work together to accomplish its goals.

This study focuses on three assessment ways which are: personality traits, team performance, and team behavioral competencies. Firstly, personality traits are recurring patterns of ideas, emotions, and actions that define a person's distinct and persistent psychological profile. These characteristics shape people's attitudes, motives, and behaviors in a variety of circumstances and contexts by affecting how they perceive and engage with the world around them. Secondly, team performance is the overall efficiency and accomplishment of a group of people working together to achieve a common goal or aim. To produce high-quality outputs and obtain desired goals, a team must be able to cooperate, communicate, and coordinate their efforts. Thirdly, behavioral competencies commonly referred to as soft skills or interpersonal skills, are a collection of personal traits, characteristics, and behaviors that enable people to work with others, carry out tasks, and achieve goals in a professional or social setting. Issues with team composition can come up while putting together a team and selecting the most compatible members to work with. Finding a balance between team dynamics and individual competencies can be difficult when putting together a team. Conflicts between team members or clashing personalities can cause a breakdown in communication, lower motivation, and lessen production. As a result, putting together a team would be simpler and more effective with the usage of the previous three assessment methods, and the results would be high quality.

III. Literature Review

Recent developments in artificial intelligence (AI) have made it possible for we-based expert systems and chatbots to become useful tools for a variety of applications. By utilizing their capacity to assess and interpret personality traits, such systems have the potential to assist companies in creating more productive teams.

According to Aonghusa and Michie [11], the use of AI in behavioral research is still in its early stages, and changing present procedures is necessary to fully realize AI's potential. AI technology offers significant potential in behavioral science by enabling researchers to analyze vast amounts of data, make predictions, simulate human behavior, and develop personalized interventions. Aonghusa and Michie [11] stated that the goal of predicting behavior change intervention results using data that is automatically retrieved from intervention evaluation reports is one that AI offers great potential for achieving. AI enables researchers in behavioral sciences to gain insights into various aspects of human behavior, improve data analysis, and enhance the understanding of complex behavioral phenomena.

A web-based expert system is a software application that applies artificial intelligence principles to deliver professional-level information and judgment through a web interface. Ramadhani et al. [12] conducted a study using knowledge-based web-based expert systems to help them achieve their goals, and the research analyses the efficacy and accuracy of the web-based expert system. Saiful and Nur [13] stated that in general, expert systems are systems that attempt to convey human knowledge to computers so that computers can solve issues the way experts often do. Data can be gathered by expert systems that keep the expertise of one or more experts on a computer. According to Thorat and Jadhav [14], a common method for managing conversations is chatbots. However, A damopoulou and Moussiades [15] stated that although chatbots can simulate human communication and amuse users; this is not their only purpose. Wolff et al. [16] and Singh et al. [17] both highlight the potential of rule-based chatbots in workplace settings, with the former identifying support and self-service as key areas of application, and the latter demonstrating the use of a rule-based chatbot for student enquiries. Handel et al. [18] provides a broader perspective on the use of synchronous messaging applications, including chatbots, in workplace teams, emphasizing their role in supporting work tasks and negotiating availability. Hwang and Won [19] further explores the potential of chatbots in team creativity, finding that participants contributed more ideas and of higher quality when they perceived their partner to be a chatbot. These studies collectively suggest that rule-based chatbots can be effectively integrated into workplace environments to facilitate team composition, support work tasks, and enhance team creativity.

Current research in web-based expert systems and team dynamics primarily focuses on the harnessing of collective intelligence for team formation and the intricate impact of these systems on job evaluation and psychological design considerations. Research on web-based expert systems and team dynamics has explored the use of collective intelligence in team formation [20], the impact of expert systems on job evaluation and decision-making [21], and the psychological issues in the design of these systems [22]. These studies highlight the potential of web-based expert systems in optimizing team dynamics by leveraging collective intelligence and providing decision support. However, there is a need for further research at the intersection of artificial intelligence and personality trait analysis to fully understand the role of these systems in team optimization.

A range of studies have explored the use of web-based expert bots to identify complementary personality traits and recommend optimal team compositions. N et al. [23] developed a recommendation engine using the Myers-Briggs Type Indicator (MBTI) and deep learning to accurately predict personality traits and suggest team compositions. Davoodi et.al. [24] proposed a hybrid expert recommendation system that considers both content-based profiles and social network-based collaborative filtering to improve recommendation accuracy. Oliveira et. al. [25] focused on a model for analyzing personality traits to support project team recommendations based on complementarity. Lastly, Gilal et al. [26] used a rule-based approach to identify effective personality types and diversity in software team roles, finding that extrovert personality types and team homogeneity or heterogeneity play key roles. These studies collectively highlight the potential of web-based expert bots in identifying complementary personality traits and recommending optimal team compositions.

IV. Methods

A. *Web-based Expert Bot System Framework*

The framework of the web-based expert system developed in this study consists of two principal components (see Fig. 1): a rule-based chatbot and a comprehensive web-based expert system. The rule-based chatbot is intricately designed with a knowledge engineer at its core, facilitating the accumulation and organization of expertise. It is supported by a robust knowledge base and specialized personality knowledge resources, which are essential for accurate personality trait analysis. An inference engine is integrated into the chatbot, enabling it to intelligently process user inputs. This chatbot functions through an interactive interface, engaging users via a series of questions and answers, thereby gathering essential data for team composition analysis. The second component of the framework extends beyond the chatbot, encompassing the company team manager and a diverse team group. This component is equipped with a dynamic assessment notification system, a comprehensive database for storing and retrieving data, and functionalities for both new assessments and reassessments of team dynamics. It specifically addresses the nuances of first-time group formations and role-specific group assemblies. The entire framework is seamlessly integrated into a user-friendly website interface, ensuring ease of access and interaction for all users, from team managers to individual team members. This dual-component framework aims to provide a thorough and interactive experience, leveraging both rule-based and expert system technologies to optimize team composition and performance in the workplace.

1) Knowledge base and personality knowledge resources: To inform the development of our knowledge base and ensure it is attuned to the needs of the workplace, a comprehensive survey was conducted. This survey targeted employers and team leaders, with the objective of gathering insights into their experiences and perspectives on the significance of personality traits, teamwork, and leadership within their organizational contexts. Respondents were presented with queries regarding teamwork dynamics, common workplace challenges, and their openness to utilizing the website developed through this research. The data collected from this survey serves as a vital component of our knowledge base, influencing the design and functionality of the expert system to better address the intricacies of workplace interactions and team efficiency.

Regarding the structural aspect of our knowledge base, this study has adopted frames as the method of knowledge representation. Frames offer a dynamic way to encapsulate knowledge about various concepts, ideas, or situations through their two fundamental elements: components and slots. Components are responsible for providing specific values for certain attributes, while slots are designed to denote the attributes or characteristics themselves. This structured approach allows for the intricate organization and representation of complex knowledge within the system. Within our knowledge base, frames have been instrumental in organizing three distinct assessment methods: personality traits assessments (X), team performance assessments (Y), and team behavioral competencies assessments (Z).

2) Knowledge engineer: A knowledge engineer is an individual who creates and develops systems to successfully gather, arrange, and use information. They make sure that knowledge is accessible to and effectively used by both humans and machines.

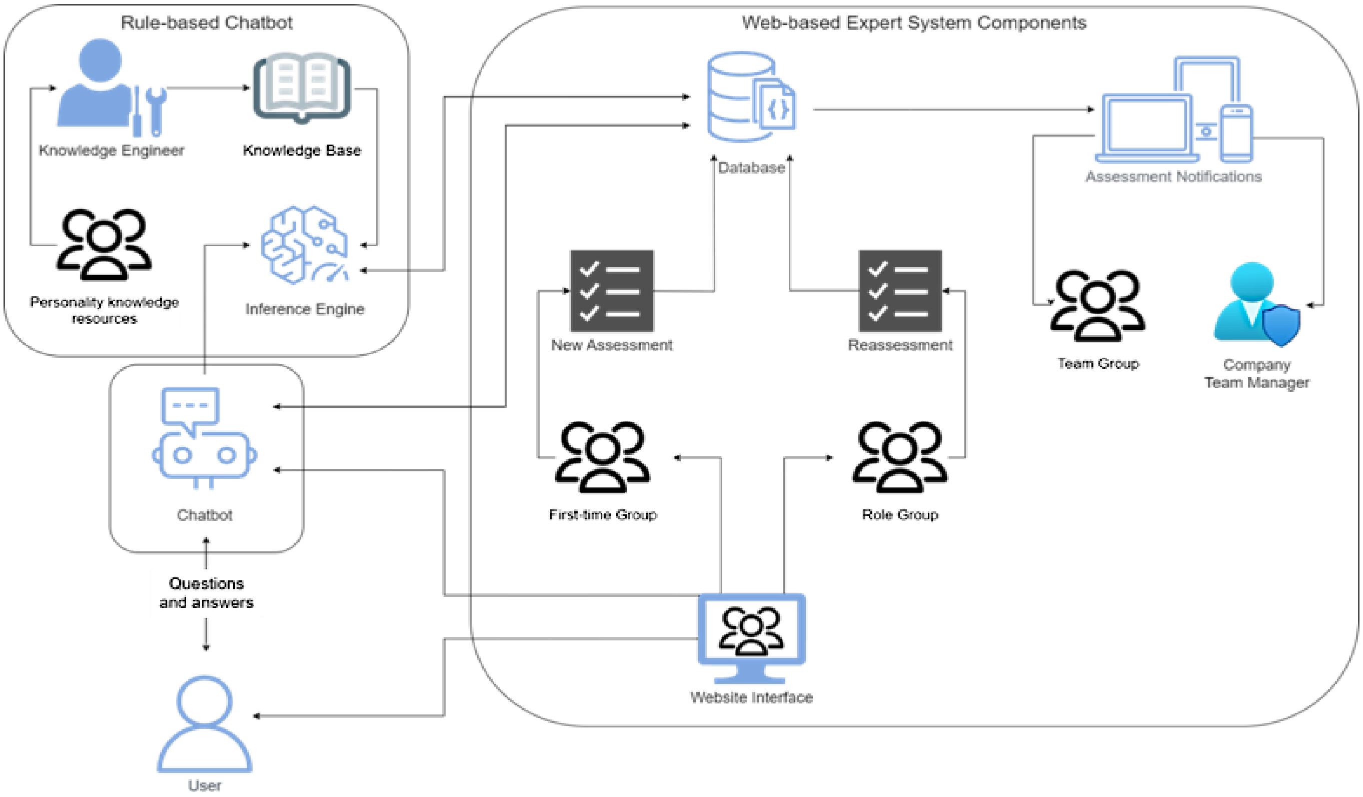


Fig. 1. Web-based expert bot system framework.

3) Inference engine: Two common methods used in inference engines to draw conclusions and make inferences based on existing knowledge are forward chaining and backward chaining. However, the forward chaining approach is the main focus of this paper. Forward chaining starts with a base set of predetermined facts or data and then applies rules that apply to those facts to produce new data. The knowledge base is expanded with the generated data, which is then used to make additional inferences.

4) Chatbot: In the context of this study, we have utilized the Landbot platform to design our chatbot. Landbot stands out as a user-friendly platform that enables the creation of conversational chatbots and interactive experiences tailored for website integration. Its appeal lies in its accessibility, as it requires no coding or technical expertise, making it an ideal choice for creating a chatbot suited to our research needs. This chatbot plays a pivotal role in our study, engaging with users in an intuitive and seamless manner, thereby facilitating the collection of data and enhancing the user experience without necessitating complex programming skills. The choice of Landbot for our chatbot design underscores our commitment to leveraging advanced yet accessible technology to achieve our research objectives effectively.

5) Database: Oracle Database is utilized to facilitate our data management requirements. Oracle Database is known for its efficiency and versatility as a proprietary multi-model database management system, produced and marketed by Oracle Corporation. It is especially suited for handling complex datasets and supporting the sophisticated queries that our study demands. Fig. 2 presents the ER schema diagram, illustrating the relational structure among the nine entities central to our study: Team, Team Member, Company, Project, Assessment Test, Assessment Results, Behavioral Competence Criteria, Team Performance Criteria, and Personality Trait Criteria. Within this structure, a Company creates a Project, which is overseen by a Team Manager. The Team Manager is responsible for assembling a Team, selected based on Assessment Results derived from Assessment Tests. The Company is tasked with establishing the Criteria for Behavioral Competence, Team Performance, and Personality Traits, which are critical for the project's success. This relational database design is crucial for capturing the intricate relationships and dependencies among these entities, ensuring that data integrity and access efficiency are maintained throughout the study.

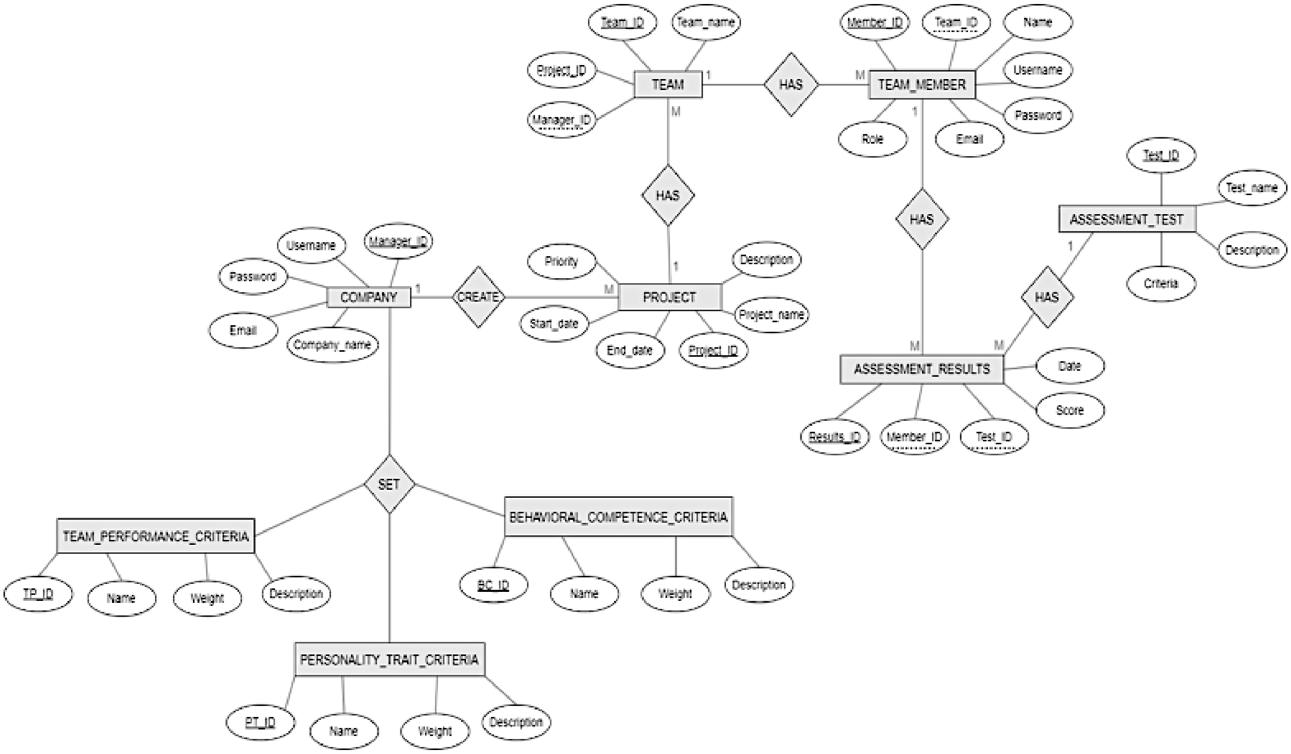


Fig. 2. The ER schema diagram.

6) User interfaces: The design considerations and functionalities of the interface are detailed from the perspectives of two types of users: the Company Team Manager and the Team Member. These roles are integral to the interaction with our web-based expert bot system and are outlined as follows:

- Company Team Manager: This user is granted comprehensive access to the company's account on the platform. The interface is designed to be intuitive, allowing the team manager to seamlessly set up and input data for projects and employee profiles. A key feature of this role is the ability to view and analyze test results from every employee, enabling the manager to make informed decisions based on the robust team recommendations generated by the system. The interface is crafted to ensure that the manager can easily navigate through various projects, manage teams, and access a holistic view of employee assessments and recommendations.

- Team Member: The team member's user interface is tailored to provide individual access to specific functionalities. Through this interface, a team member can receive and respond to tests dispatched by the company's team manager. Post-assessment, the interface allows team members to view their own personality assessments and understand the context of their roles within the team's recommendations. The design of the team member interface is focused on user-friendliness and personal data security, ensuring that team members can engage with the assessment process in a straightforward and secure manner.

To encapsulate the various interactions each user type will have with our system, Table I is provided, which details user types and their corresponding functions. This table serves as a reference for the access levels and capabilities that each user type possesses, ensuring clarity in the system's functionality and user privileges. The user interface is developed with a focus on clarity and ease of use, to facilitate efficient interaction with the system's comprehensive functionalities.

B. Prototype

For this study, we have utilized Proto.io, a highly versatile platform that specializes in creating interactive and high-fidelity prototypes for websites. Proto.io has enabled us to design and iterate upon our website's prototype rapidly, allowing us to explore various user interface designs and functionalities in a real-world, interactive environment. This approach has been instrumental in refining our concept into a tangible and testable product. By using Proto.io, we have effectively bridged the gap between theoretical design and practical application, providing us with valuable insights into user experience and system performance prior to the full-scale development and deployment of the system.

V. Results

A. Knowledge Base and Personality Knowledge

The findings from a survey was presented to understand the perceptions of employers and team leaders regarding the dynamics of the workplace. This survey, which gathered around 140 responses, probed the value placed on personality traits, teamwork, and leadership, and evaluated the potential adoption of the research website developed for team composition and management. A significant majority of participants, 59.6%, affirmed that effective teamwork stands out as one of the paramount strengths within a workplace, as highlighted in question (1) of the survey. Delving into the challenges of teamwork, question (6) revealed a compelling consensus with 93.6% of respondents agreeing that conflicts among team members are a predominant barrier to meeting organizational goals. Further insights from question (7) indicated that 37.6% of respondents attribute team member conflicts to ineffective leadership and management, while 27% cited personality clashes as a crucial factor, thereby substantiating the rationale behind this research.

Moreover, the survey brought to light a near-universal acknowledgment of the uniqueness of individual personality attributes, with 99.3% of respondents concurring with this view in response to question (9). This perspective is complemented by findings from question (2), where 49.6% of participants identified poor leadership as a pivotal issue in failing to achieve goals. Question (8) underscored the eagerness of leaders to understand the personality traits of their team members, with a remarkable 97.9% expressing the desire to gain a deeper insight into their teams.

Finally, the concept of the research website garnered robust support, with over 85% of respondents affirming the utility of such a tool in questions (10) and (11). This overwhelming approval validates the direction and objectives of our research, highlighting the demand for innovative solutions in understanding and harnessing the potential of workplace dynamics. The results from the survey are not only reflective of current workplace sentiments but also reinforce the need for the tools and analyses provided by our web-based expert system in optimizing team performance. Read A1 section of the supplement file for detailed survey results while the following were the survey questions:

1) *What* is the strongest strength of any workplace?

2) *What* is a big reason for not achieving goals at work?

3) *Do* you think that communication is one of the reasons for failure to achieve goals?

4) *What* is the most basic skill for achieving effective communication?

5) *Do* you think that misunderstanding and miscommunication are due to your lack of understanding of the other person?

6) *Do* you think that one of the reasons for the failure of work teams to achieve goals is due to conflicts and differences between team members?

7) *What* do you think the most important reason for differences and conflicts among team members?

8) *If* you have a project to complete and you are the team leader, do you think it is important to understand the personalities of the team members so that it is easier for you to distribute tasks?

9) *Do* you believe that every individual has a personality?

10) *If* there was a website that studied the personalities of your employees, would you use it?

11) *If* there is a website that helps a manager achieve the goals of a project through analyzing the project, its objectives, its implementation plan, and analyzing the personalities who help in completing the project, would you use it?

In this research, the decision to not collect demographic information was deliberate and based on several considerations. First and foremost, the focus of the study was to gauge attitudes and opinions on teamwork and leadership in the workplace, which are aspects that transcend demographic categories such as age, gender, or ethnicity. By omitting demographic questions, we aimed to prevent any potential bias that could arise from preconceived notions about certain demographic groups and their relationship with the workplace dynamics being studied. Furthermore, the anonymity of responses was prioritized to ensure that participants felt comfortable sharing honest opinions without concern for personal identifiers being used in the analysis. This approach was intended to enhance the integrity and applicability of the data across diverse workplace settings, making the findings more universally relevant and reducing the risk of demographic data skewing the interpretation of the core research questions.

TABLE I. USERS TYPE AND THE RELATED FUNCTIONS

Users Type	Functions
Company team manager	1. Sign in/up to the company's account as a manager. 2. Fill out the manager's personal information. 3. Set employee criteria, the weight of each criterion. 4. Set project requirements (project name, description, start date, end date, and priority). 5. Set team information. 6. Send the assessment test link to employees. 7. Display the team recommendations.
Team member	1. Sign in/up to the company’s account as an employee. 2. Fill out personal information. 3. Display test results. 4. Receive assessments test (new or retake). 5. Receive team recommendations. 6. Display registered team. 7. Receive notification if chosen for the team.

Fig. 3 provides a detailed visual representation of the architecture underlying the knowledge base and personality knowledge resources utilized in our study. It meticulously outlines how frames are employed to structure and organize the complex information integral to the research. These frames act as the building blocks of our knowledge base, enabling us to systematically categorize and access data on personality traits, team performance, and behavioral competencies. The figure serves to demonstrate the interconnectivity and flow of information within the system, ensuring that data retrieval is both logical and efficient. For an in-depth understanding of the specific personality knowledge frames, read section A2 of the supplementary files, where each frame is delineated, providing transparency and further insight into the foundational elements that support our expert system. This delineation is crucial for appreciating the sophistication and nuance of the system's design and its capacity for contributing to the field of team dynamics and organizational psychology.

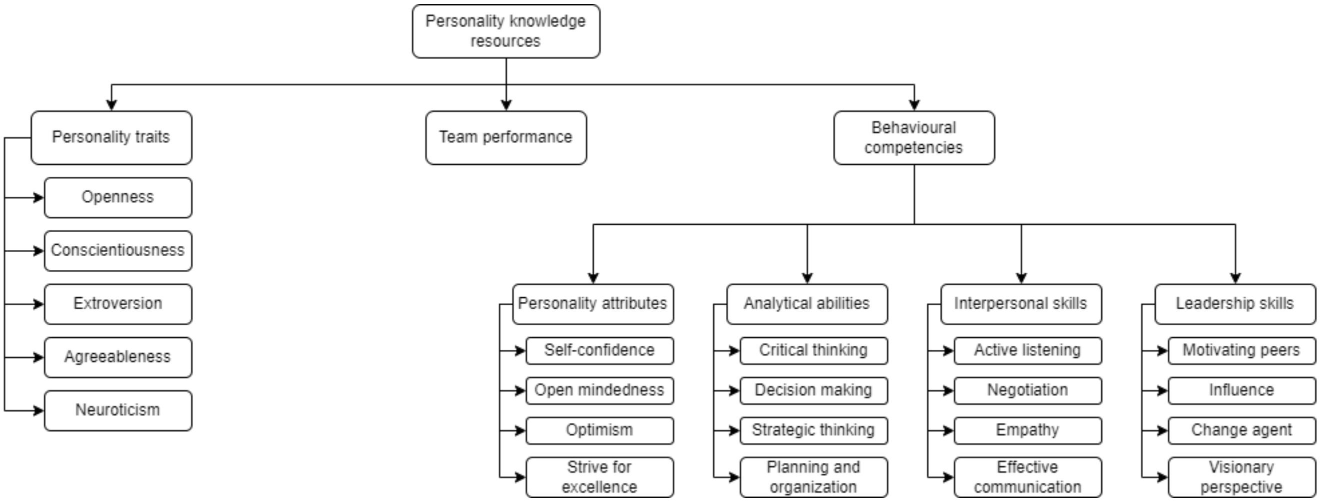
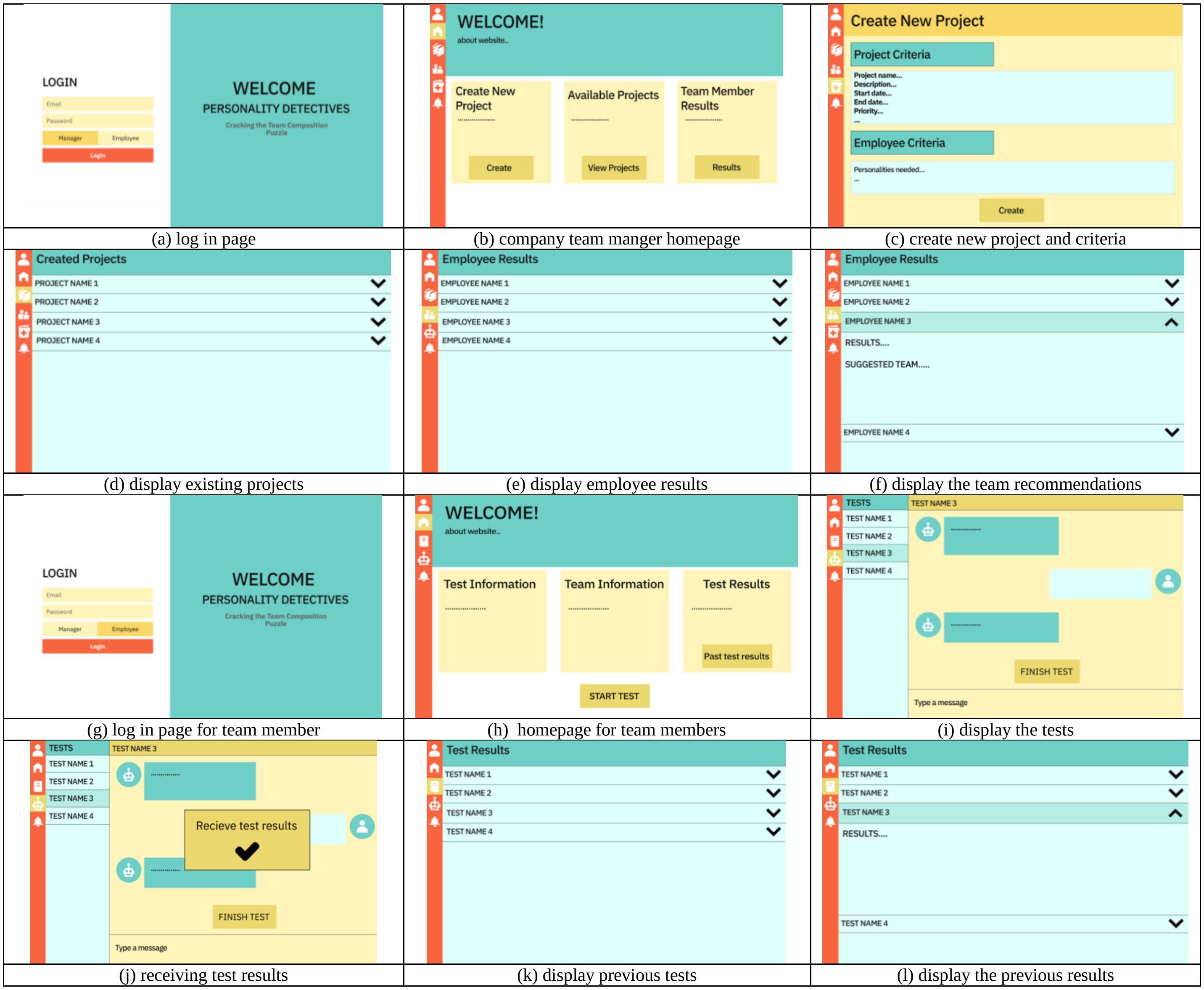


Fig. 3. The components of the knowledge base and personality knowledge.



(a) log in page
(b) company team manger homepage
(c) create new project and criteria
(d) display existing projects
(e) display employee results
(f) display the team recommendations
(g) log in page for team member
(h) homepage for team members
(i) display the tests
(j) receiving test results
(k) display previous tests
(l) display the previous results

Fig. 4. Web-based expert bot system user interfaces.

B. Web-based Expert Bot System Prototype

The prototype of the Web-based Expert Bot System is presented, focusing on its user interface design for two distinct user roles: the Team Member and the Team Manager. Fig. 4 provides a comprehensive visual breakdown of the user interfaces, meticulously detailing the functionalities and navigational flow tailored to each type of user. The interfaces designated for the Company Team Manager are showed in print screen (a) through (f) of Fig. 4. These segments illustrate the breadth of control and oversight that a team manager possesses within the system, from project initiation and data management to team assessment and recommendations. On the other hand, the Team Member's interface is presented in printscreen (g) through (l), emphasizing the user-centric design that provides team members with access to personality assessments, team evaluations, and managerial feedback. This delineation within Fig. 4 not only demonstrates the system's dual-interface capability but also highlights the intuitive design and functionality that cater to the specific needs and roles of the users within a team-oriented workplace setting.

C. Chatbot Prototype

The development of the chatbot prototype plays a significant role using the Landbot platform, this prototype exemplifies a user-friendly approach to engaging with users in an interactive and conversational manner. One of the key features of our chatbot is its integration of personality knowledge, which is crucial for identifying and administering personality tests in an accessible and engaging way.

Through this chatbot, users are navigated through a series of questions enabling the system to gather essential information on individual personality traits. The design of the chatbot prioritizes ease of use and interactivity, ensuring that users can participate in the assessment process without the need for extensive instructions or guidance. This approach not only enhances user engagement but also improves the accuracy and relevance of the data collected.

For a more comprehensive understanding of how the chatbot functions and interacts with users, we invite readers to explore the live prototype available at (https://landbot.online/v3/H-1692227-0Q820B5ZRGJJXKW7/index.html).

VI. Discussion

The development of a web-based expert bot system, augmented by a chatbot interface, for evaluating and synthesizing employee personality profiles can offer several advantages. Research has shown that incorporating personality into chatbot design can significantly improve user experience [27]. This is particularly relevant in the context of employee mental health assessments, where chatbots have been found to be highly engaging and effective [28]. Furthermore, the use of chatbots with distinct personalities can enhance the naturalness and effectiveness of the system [29]. Therefore, the proposed system has the potential to not only improve team alignment but also enhance user experience and engagement.

Acknowledging the limitations of our research is vital to contextualize our findings within the scope of their applicability. In our study, the use of a web-based expert bot system for enhancing workplace team dynamics is an innovative approach; however, it is not without constraints. Primarily, the system's reliance on self-reported data could introduce biases, as participants might provide socially desirable responses rather than accurate portrayals of their personality traits. Additionally, while our sample size was adequate to establish preliminary insights, a larger and more diverse cohort would be necessary to affirm the robustness of our findings across different industries and organizational cultures. Our framework's current configuration is tailored to specific personality models and team roles, which might not be universally applicable or reflective of all workplace environments. Future research could focus on expanding the adaptability of the system to include a broader range of psychological theories and occupational settings. Moreover, as our study is cross-sectional, it limits the ability to infer causality between team composition and performance outcomes. Longitudinal studies could provide a deeper understanding of these dynamics over time. By addressing these limitations in subsequent research, we can refine the application of expert bot systems to more accurately predict and enhance team performance.

VII. Conclusion

The conclusion of this study underscores the critical importance of building effective teams for companies looking to optimize production and foster innovation. The interplay between individual personality traits and team dynamics plays a significant role in team performance, warranting thorough examination and understanding. While numerous studies have investigated these elements, this research extends the discourse by incorporating a knowledge-based system and a rule-based chatbot into the organizational environment.

Our findings illuminate the transformative potential of web-based expert bot systems in assembling more productive teams. By leveraging the systems' sophisticated capabilities to identify complementary personality traits and assess team performance and behavioral competencies, organizations are empowered to make informed, data-driven decisions. This approach facilitates enhanced team dynamics, elevates performance levels, and ensures a more effective allocation of organizational resources.

However, the adoption of these technologies is not without its challenges. To truly reap their benefits and mitigate any potential drawbacks, a deliberate and informed implementation strategy is essential. Further research is also necessary to continue refining these systems, addressing any issues that arise, and expanding their applicability within diverse organizational contexts. In this pursuit, the future of work may be shaped by a more intelligent, intuitive, and data-oriented approach to team composition and management.

Authors' Contributions

Conceptualization, H.B. and M.F.; Methodology, H.B. and M.F.; Software, M.F.; Validation, H.B. and M.F.; Investigation, M.F.; Resources, H.B. and M.F.; Data

Curation, M.F.; Writing – Original Draft Preparation, M.F. ; Writing – Review & Editing, H.B. and M.F.; Visualization, M.F.; Supervision, H.B.; Project Administration, H.B.; Funding Acquisition, H.B.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare.

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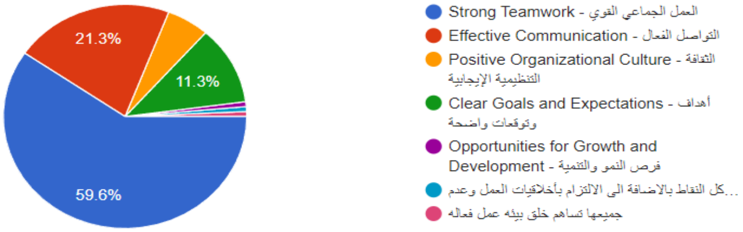
SUPPLEMENTARY MATERIAL

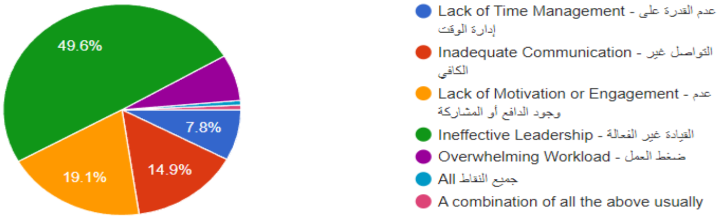
Supplementary Material: Knowledge base and personality knowledge

A. *Survey Results*

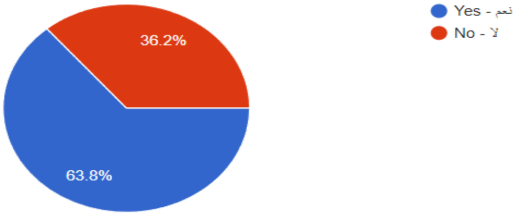
12) What is the strongest strength of any workplace?



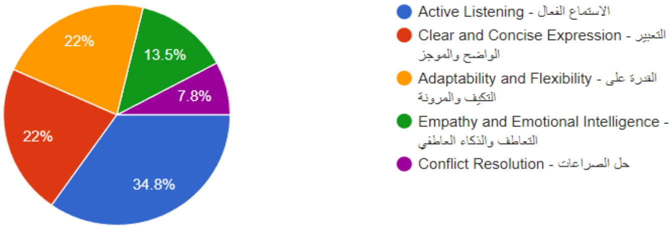
13) What is a big reason for not achieving goals at work?



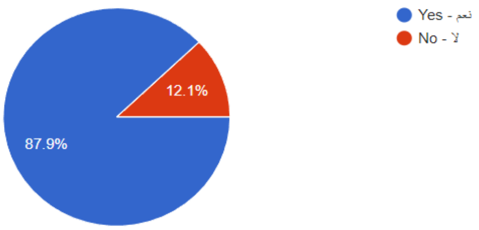
14) Do you think that communication is one of the reasons for failure to achieve goals?



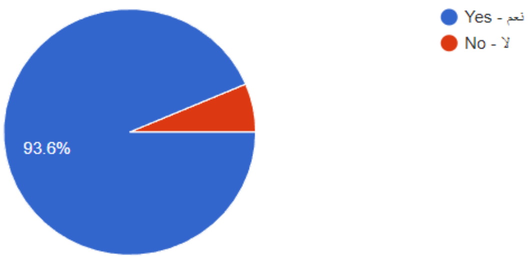
15) What is the most basic skill for achieving effective communication?



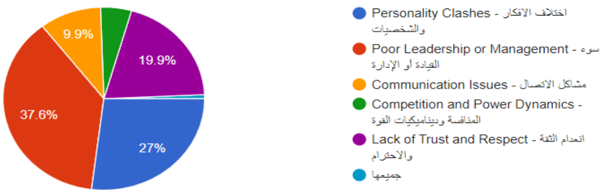
16) Do you think that misunderstanding and miscommunication are due to your lack of understanding of the other person?



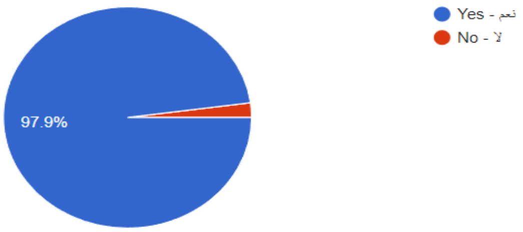
17) Do you think that one of the reasons for the failure of work teams to achieve goals is due to conflicts and differences between team members?



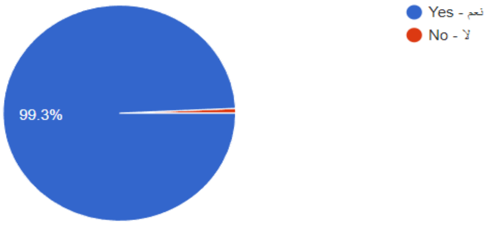
18) What do you think the most important reason for differences and conflicts among team members?



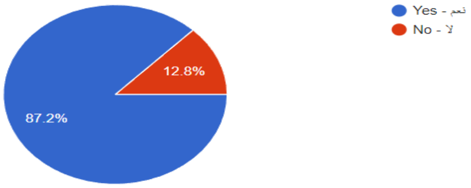
19) If you have a project to complete and you are the team leader, do you think it is important to understand the personalities of the team members so that it is easier for you to distribute tasks?



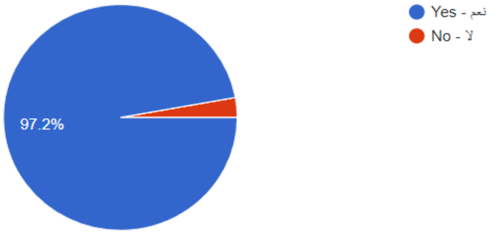
20) Do you believe that every individual has a personality?



21) If there was a website that studied the personalities of your employees, would you use it?



22) If there is a website that helps a manager achieve the goals of a project through analyzing the project, its objectives, its implementation plan, and analyzing the personalities who help in completing the project, would you use it?



A2. Personality Knowledge Frames

Assessment	Phases	Variables		Questions	Possible answers	Chatbot output
Personality traits	Phase 1	Personality trait 1: Openness		1. I see myself as someone who is original, unique, and comes up with new ideas. 2. I see myself as someone who is curious about many different things. 3. I see myself as someone who is sophisticated in art, music, or literature. 4. I see myself as someone who has a lot of artistic interests. 5. I see myself as someone who has an active imagination. 6. I see myself as someone who values artistic and creative experiences. 7. I see myself as someone who is inventive.	yes>=4	You have the “openness” personality trait.
					yes<4	You do not have the “openness” personality trait.
	Phase 2	Personality trait 2: Conscientiousness		1. I see myself as someone who does a thorough job. 2. I see myself as someone who is extremely careful. 3. I see myself as someone who is a reliable worker. 4. I see myself as someone who tends to be organized. 5. I see myself as someone who tends to be diligent. 6. I see myself as someone who perseveres until the task is finished. 7. I see myself as someone who does things efficiently. 8. I see myself as someone who prefers work that is routine. 9. I see myself as someone who is cerebral and enjoys thinking deeply. 10. I see myself as someone who makes plans and follows through with them. 11. I see myself as someone who is not easily distracted.	yes>=6	You have the “conscientiousness” personality trait.
					yes<6	You do not have the “conscientiousness” personality trait.
	Phase 3	Personality trait 3: Extroversion		1. I see myself as someone who is outgoing. 2. I see myself as someone who is full of energy. 3. I see myself as someone who generates a lot of enthusiasm. 4. I see myself as someone who tends to be loud. 5. I see myself as someone who has an assertive personality. 6. I see myself as someone who can be warm and friendly. 7. I see myself as someone who likes to reflect and ponder different ideas. 8. I see myself as someone who is outgoing and sociable. 9. I see myself as someone who is talkative.	yes>=5	You have the “extroversion” personality trait.
					yes<5	You do not have the “extroversion” personality trait.
	Phase 4	Personality trait 4: Agreeableness		1.I see myself as someone who is helpful and unselfish when it comes to others. 2. I see myself as someone who avoids arguments with others. 3. I see myself as someone who has a forgiving nature. 4. I see myself as someone who is considerate and kind to almost everyone. 5. I see myself as someone who likes to cooperate with others. 6. I see myself as someone who is rarely rude to others. 7. I see myself as someone who is generally trusting. 8. I see myself as someone who does not look for fault in others.	yes>=5	You have the “agreeableness” personality trait.
					yes<5	You do not have the “agreeableness” personality trait.
	Phase 5	Personality trait 5: Neuroticism		1. I see myself as someone who is depressed. 2. I see myself as someone who can be tense. 3. I see myself as someone who worries a lot. 4. I see myself as someone who is emotionally stable and doesn't get upset easily. 5. I see myself as someone who can be moody. 6. I see myself as someone who is sometimes shy and inhibited.	yes>=5	You have the “neuroticism” personality trait.
					yes<5	You do not have the “neuroticism” personality trait.

				7. I see myself as someone who gets nervous easily. 8. I see myself as someone who does not remain calm in high-pressure situations. 9. I see myself as someone who does not remain calm in tense situations.		
Team performance	Phase 6			1. Do you provide regular feedback and guidance to help improve team performance? 2. Are you able to identify and leverage the strengths of your team members to enhance overall performance? 3. Are you able to address and resolve conflicts or issues that may impact team performance? 4. Are you able to identify and address any barriers or challenges that may hinder team performance? 5. Do you set clear performance expectations for your team members?	yes>=3	You have team performance traits. Proceed to phase 7
					yes<3	Proceed to phase 7
Team behavioral competence	Phase 7	1-Personality attributes	PA 1: Self-confidence	1. Do you generally feel confident when facing new challenges? 2. Do you tend to trust your abilities and judgment in decision-making? 3. Can setbacks or failures shake your self-confidence easily? 4. Do you feel comfortable expressing your opinions and ideas in group settings? 5. Do you find it easier to take risks when you have a high level of self-confidence?	yes>=3	Proceed to next part
					yes<3	
			PA 2: Open mindedness	1. Are you open to considering different perspectives and opinions? 2. Do you actively seek out new experiences and ideas? 3. Do you enjoy engaging in discussions with people who have different viewpoints? 4. Do you find it easy to adapt to new situations and environments? 5. Are you willing to change your beliefs or opinions when presented with new evidence?	yes>=3	Proceed to next part
					yes<3	
			PA 3: Optimism	1. Do you generally maintain a positive outlook on life? 2. Are you generally hopeful about the outcomes of your efforts? 3. Do you tend to focus on solutions rather than dwelling on problems? 4. Are you able to maintain an optimistic attitude even in the face of uncertainty? 5. Do you believe that setbacks are temporary and can lead to growth and learning?	yes>=3	Proceed to next part
					yes<3	
			PA 4: Strive for excellence	1. Do you consistently set high standards for yourself? 2. Are you motivated to constantly improve and achieve your personal best? 3. Are you willing to put in extra effort to achieve exceptional results? 4. Are you driven by a desire to surpass expectations? 5. Are you willing to go above and beyond what is expected of you?	yes>=3	You have _/4 of personality attributes.
					yes<3	Proceed to phase 8
	Phase 8	2-Analytical abilities	AA 1: Critical thinking	1. Are you skilled at analyzing complex problems and breaking them down into manageable parts? 2. Are you able to identify logical inconsistencies or flaws in arguments? 3. Can you effectively separate facts from opinions or biases? 4. Are you open to changing your beliefs based on new evidence or persuasive arguments? 5. Do you question assumptions and seek evidence before forming conclusions?	yes>=3	Proceed to next part
					yes<3	
			AA 2: Planning and organization	1. Do you create detailed plans and schedules to guide your work? 2. Are you able to prioritize tasks effectively based on their importance and urgency? 3. Are you skilled at breaking down complex projects	yes>=3	Proceed to next part
					yes<3	

				into smaller, manageable tasks? 4. Are you able to meet deadlines consistently through effective planning and time management? 5. Do you value planning and organization as important factors in achieving success?		
			AA 3: Decision making	1. Do you carefully consider available options before making decisions? 2. Are you comfortable with making decisions based on data and evidence? 3. Do you weigh the potential risks and benefits before making a decision? 4. Are you able to analyze and evaluate the potential outcomes of different choices? 5. Are you able to make decisions efficiently, even under time constraints?	yes>=3	Proceed to next part
					yes<3	
			AA4: Strategic thinking	1. Do you consider the long-term implications and consequences of your actions? 2. Do you proactively identify opportunities and challenges that may arise in the future? 3. Are you able to develop and communicate a clear vision for achieving desired outcomes? 4. Are you skilled at analyzing trends and patterns to inform strategic decisions? 5. Do you consider multiple possible scenarios and their potential outcomes when making decisions?	yes>=3	You have _/4 of analytical abilities.
					yes<3	Proceed to phase 9
	Phase 9	3-Interpersonal skills	IS 1: Effective communication	1. Are you able to clearly articulate your thoughts and ideas? 2. Are you skilled at adapting your communication style to different audiences? 3. Are you able to resolve conflicts and negotiate with others through communication? 4. Do you ask clarifying questions to ensure understanding during conversations? 5. Are you able to convey information in a concise and organized manner?	yes>=3	Proceed to next part
					yes<3	
			IS 2: Active listening	1. Do you focus your attention on the speaker and avoid distractions when engaging in a conversation? 2. Do you refrain from interrupting or speaking over others when they are expressing their thoughts? 3. Do you ask relevant and probing questions to gain further clarity and encourage the speaker to share more? 4. Are you patient and willing to give the speaker sufficient time to express their thoughts fully? 5. Are you able to maintain eye contact and show nonverbal cues that indicate your active listening?	yes>=3	Proceed to next part
					yes<3	
			IS 3: Empathy	1. Do you actively listen to others to understand their emotions and experiences? 2. Are you able to put yourself in someone else's shoes to see things from their perspective? 3. Do you show genuine care and concern for the well-being of others? 4. Are you able to detect subtle cues and signals to understand how others are feeling? 5. Are you skilled at providing emotional support and encouragement to others?	yes>=3	Proceed to next part
					yes<3	
			IS 4: Negotiation	1. Are you skilled at finding common ground and areas of agreement during negotiations? 2. Are you able to effectively communicate your own needs and interests during negotiations? 3. Are you able to manage conflicts and reach compromises during negotiations? 4. Do you listen actively to the perspectives and concerns of the other party during negotiations? 5. Are you able to identify and understand the needs and interests of others during negotiations?	yes>=3	You have _/4 of interpersonal skills.
					yes<3	Proceed to next phase 10

	Phase 10	4-Leadership skills	LS 1: Motivating peers	1. Do you actively encourage and inspire your peers to achieve their best? 2. Are you able to identify and leverage the strengths of your peers to motivate them? 3. Do you offer support and guidance to help your peers overcome obstacles and challenges? 4. Do you lead by example, displaying a high level of motivation and enthusiasm yourself? 5. Are you able to effectively communicate the purpose and vision of the team to motivate your peers?	yes>=3	Proceed to next part
					yes<3	
			LS 2: Influence	1. Are you able to effectively persuade and convince others to adopt your ideas or viewpoints? 2. Are you skilled at building strong relationships and networks that allow you to influence others? 3. Do you have the ability to inspire and motivate others to take action? 4. Are you able to adapt your communication style to connect with different individuals and groups? 5. Are you comfortable challenging the status quo and proposing innovative ideas to influence change?	yes>=3	Proceed to next part
					yes<3	
			LS 3: Visionary perspective	1. Do you have a clear and inspiring vision for the future of your team or organization? 2. Do you regularly assess and reassess your vision to ensure it remains relevant and aligned with changing circumstances? 3. Do you actively seek input and feedback from others to shape and refine your vision? 4. Are you able to break down your vision into actionable steps and goals? 5. Are you able to effectively communicate your vision to others?	yes>=3	Proceed to next part
					yes<3	
			LS 4: Change agent	1. Do you actively seek opportunities to drive positive change within your team or organization? 2. Do you lead by example, demonstrating a willingness to embrace and adapt to change yourself? 3. Do you value continuous improvement and actively seek ways to innovate and evolve? 4. Do you encourage and support others in embracing and adapting to change? 5. Are you skilled at identifying and addressing resistance to change?	yes>=3	You have _/4 of leadership skills.
					yes<3	FINISH

Hybrid Intrusion Detection System Based on Data Resampling and Deep Learning

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***Abstract*—The growth of the internet has advanced information-sharing capabilities and vastly increased the importance of global network security. However, because new and inconspicuous abnormal behaviors are nearly impossible to detect in massive network access environments, modern intrusion detection systems have identified a high rate of false-positive (FP) and false-negative (FN) attacks. To overcome this, this paper proposes a hybrid deep learning model that significantly mitigates the disadvantages of consistently imbalanced sample attack data. First, it resolves imbalanced data using random undersampling and synthetic minority oversampling techniques. Then, convolutional neural networks (CNNs) extract local and spatial features, and a transformer encoder extracts global and temporal features. The novelty of this combination increases recognition accuracy at the algorithm level, which is crucial to reducing FPs and FNs. The model was subjected to multiclassification testing on the NSL-KDD and CICIDS2017 benchmark datasets, and the results show that our model has higher classification accuracy and lower FP rates than state-of-the-art intrusion detection models. Moreover, it significantly improves the detection rate of low-frequency attacks.**

Keywords—Intrusion detection; deep learning; random undersampling; synthetic minority oversampling technique; convolutional neural network; transformer

I. Introduction

The ubiquity of mobile handheld internet devices allows people to access digital information quickly and effortlessly, just about anywhere. The associated transference and storage of vast volumes of data over computer networks have created new and evolving opportunities for cybercriminals [1]. From 2019 to 2022, the cost of repairing cyberattack damage increased by USD 6T, and the average detection time increased from 57.4 to 93.2 days [2]. Traditional cybersecurity methods (e.g., firewalls, user authentication, and data encryption) cannot handle the complex attacks that take place online. Intrusion detection systems (IDSs) are designed to detect a variety of anomalous patterns that serve as the attack signatures of new and known attacks [3], using advanced database systems with machine learning [4]. When an IDS reports potential malicious activities in an information system [5], it kicks off various analytical and alerting processes to confirm the nature of the attack and launch protection measures.

IDSs generally operate in three phases: information collection, data analysis, and response. The fact that most advanced cyberattacks utilize new and unusual network and system penetration methods makes it nearly impossible to train machine learning models to recognize discrete new and seemingly inconspicuous threats. On the other hand, the models must still be trained with legacy class types from past attacks. Hence, IDS training datasets grow heavily imbalanced over time [6]. Supposing the target class is rare (< 10%) in terms of its representation in the training dataset, critical new and unusual network behaviors can be easily overlooked (as with human perception).

Modern machine-learning methods that handle unbalanced classes typically consider both data- and algorithm-level remedies. That is, training data and classification algorithms are modified separately so that their combination will improve the detection and recognition accuracy of minority samples. Hence, advantageous tradeoffs can be gained. Unfortunately, even the most state-of-the-art IDS models continue to suffer high rates of false-positive (FP) and false-negative (FN) attack detection.

To contribute to the robustness of machine-learning IDS accuracy and recognition, this study makes the following contributions. (1) We apply a novel combination of data- and algorithm-level techniques to specifically reduce the FP rate while improving the model's recall rate. (2) We provide legitimate and reproducible results by applying our combined model to state-of-the-art NSL-KDD [7] and CICIDS2017 [8] benchmark intrusion detection datasets as our research objects. (3) To improve data-level class balancing, we provide an ingenious combination of random undersampling (RUS) and synthetic minority oversampling to adjust the data distribution structure and improve minority class detection. (4) To improve algorithm-level class balancing, we apply a hybrid convolutional neural network (CNN) and a Transformer model to adopt new detection performance efficiencies over contemporary models.

Our model's performance is compared with that of state-of-the-art IDS models, demonstrating that our innovations have clear advantages in terms of accuracy, FP rate, and recall.

To convincingly deliver this information, the remainder of this paper proceeds as follows. Section II covers the extant research that has led us to pursue our current motivations. Section III adequately describes the proposed model and the related techniques and technologies applied. Section IV describes our experiments and presents the comparison results,

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configurational impacts, and implications of our findings. Finally, Section V presents the conclusions.

II. Related Works

This study provides an IDS model that can more accurately identify malicious traffic and detect a wider variety of intrusion attacks than current models. First, our model resolves sample imbalance problems at the data and algorithm levels based on the lessons learned from current studies, described briefly in the following sections.

A. Data-Level Mitigation Efforts

In terms of the current data-level mitigation efforts used to overcome problems related to training models with imbalanced datasets, data reconstruction efforts prevail. Related strategies focus on preprocessing original datasets to provide appropriately weighted training sets for model learning and tailoring the model's feature classification methods to maximize learning and retention based on the task at hand.

A healthy number of intrepid researchers have applied oversampling [9-14], undersampling [15-19], and hybrid [20-23] preprocessing methods to restore balance to their training datasets. These methods are combined with feature classification methods to maximize benefits. For example, the synthetic minority oversampling technique (SMOTE) [24] is a widely used data reconstruction strategy that provides good data balancing and classification results while effectively avoiding overfitting. Noting that the SMOTE algorithm analyzes minority class samples and manually synthesizes new ones based on the needed additions, Dablain et al. [25] provided a deep learning-based SMOTE method that applies a novel oversampling method to counter class imbalances and train new skew-insensitive classifiers. Joloudari et al. [26] proposed a CNN that uses SMOTE to achieve a remarkable accuracy of 99.08% on 24 imbalanced datasets, including KEEL, Breast Cancer, and Z-Alizadeh Sani sets.

B. Algorithm-Level Mitigation Efforts

Most current algorithm-level mitigation efforts aim to intuitively process input data algorithmically for better classification results. Modern techniques match the model's internal structure to the distribution characteristics of the original dataset as much as possible. For example, CNN-based autoencoders are extensively used for IDSs, resulting in high detection performance [27]. Yin et al. [28] proposed a recurrent neural network (RNN)-based IDS that provides impressive breakthroughs in accuracy. Vigneswaran et al. [29] used a deep neural network (DNN) to predict attacks directed at network IDSs (NIDS). The famous KDD-CUP99 [30] dataset was used to train and benchmark, revealing that a DNN with three layers outperformed all other classical machine learning algorithms at the time. XIAO et al. [31] proposed IDS to reduce the required CNN features for computational efficiency. The KDD-CUP99 dataset was again used, showing reduced FPs and improved speeds. Belarbi et al. [32] proposed a multi-class NIDS based on a deep belief network (DBN) using the CICIDS2017 dataset to train and evaluate performance. The experimental results demonstrated that DBNs can surpass traditional multilayer perceptron classification performance, significantly improving overall recall. In 2017, Vaswani et al. [33] proposed the transformer model, originally designed to solve the tasks of language modeling and machine translation, achieving good results; this model has also been gradually applied to network IDSs. Wang et al. [34] proposed a robust unsupervised IDS (RUIDS) by introducing a masked context reconstruction module into a transformer-based, self-supervised learning scheme. Extensive experiments on four intrusion datasets were conducted to demonstrate the effectiveness and robustness of the RUIDS. Yang et al. [5] proposed IDS based on an improved vision transformer, demonstrating superior results on the NSL-KDD public intrusion detection via simulation experiments.

C. Hybrid Solutions

As noted, CNNs, RNNs, (Recurrent Neural Networks) and DBNs (Deep Belief Networks) are among the most common IDS solutions used to mitigate imbalanced data problems [36]. Hybrid models have recently become popular, based on their observed improvements to symbiotic and amplified model strength [37]. Indeed, research has shown that combined models consistently perform better than individual algorithms [38]. Table I list the best representative hybrid IDS models and summarize their basic algorithmic models, dataset properties, classification types, and accuracy results. This listing is fully explained in the subsequent narrative.

1) Focused neural network combinations: Zhang et al. [39] proposed an IDS model based on an improved genetic algorithm with a DBN trained and evaluated using the NSL-KDD dataset, demonstrating effective improvements in intrusion recognition rates (> 99%). Wu et al. [40] proposed a hierarchical CNN + RNN model (i.e., LuNet) that effectively extracts spatial and temporal data features, providing higher detection accuracy and fewer FPs than peer methods. LuNet's verification accuracies on the NSL-KDD and UNSW-NB15 datasets were 99.24% and 97.40%, respectively. Souza et al. [41] proposed a hybrid binary classification model comprising a DNN with a k-nearest-neighbors (kNN) function. This method achieved higher accuracy than classical machine learning methods, with 99.77% on the NSL-KDD dataset and 99.85% on the CICIDS2017 dataset. Albahar et al. [42] proposed an approach that combines a regularization algorithm with an artificial neural network, achieving all-time-high true-positive (TP) and accuracy rates on the NSL-KDD, UNSW-NB15, and CIDDS-001 datasets (i.e., 98.53, 94.58, and 97.87%, respectively) using 10-fold cross-validation. Ahsan et al. [43] proposed a hybrid CNN with a long short-term memory (LSTM) network, achieving the highest known accuracy (at the time) of 99.70% on the NSL-KDD dataset. Banaamah et al. [44] adopted a CNN with an LSTM and a gated recursive unit (GRU) model to improve internet-of-things (IoT) security. Using the highly reputable Bot-IoT dataset, the proposed model surpassed the highest accuracy, with a 99.8% ratio. Kamalakkannan et al. [45] developed an improved CNN + LSTM model that learns spatial and temporal data characteristics, demonstrating 98% accuracy and a 98.14% average detection rate on the NSL-KDD dataset.

Shivhare et al. [46] proposed a CNN + LSTM + SVM model to tackle multiclass tasks on the CICIDS 2017 dataset, achieving an accuracy of 97.29%. Qazi et al. [47] proposed a deep-layered CNN + RNN model to detect and classify malicious traffic using the CICIDS-2018 dataset, achieving an average accuracy of 98.90%. Recently, the use of transformers has provided new feature extraction methods. Transformers are deep neural networks wholly based on attention mechanisms that have shown great success in natural language processing (NLP) fields. Their versatility allows them to be applied to other domains, such as image classification, cybersecurity, and more. Xing et al. [48] sought to improve unknown attack learning and detection by extracting data features from different perspectives using CNN and transformer models. Xiang et al. [49] later proposed a transformer-based fusion deep learning architecture in which the transformer is used to adjust the ML-CNN-BiLSTM model to enhance its feature encoding ability. Ullah et al. [50] proposed an IDS using transformer-based transfer learning for imbalanced network traffic (INT). The resulting DS-INT uses transformer-based transfer learning to learn feature interactions in network feature representations, even with imbalanced data. A hybrid CNN-LSTM model was then developed to detect attacks from deep features.

TABLE I. SUMMARY OF THE HYBRID INTRUSION DETECTION SYSTEM

Ref.	Year	Authors	Classification Algorithms	Dataset	Classes	Accuracy (%)
[39]	2019	Zhang et al.	DBN, Impr. Genetic	NSL-KDD	Multiclass	>99.00
[40]	2019	Wu et al.	CNN, RNN	NSL-KDD	Binary, Multiclass	99.24 (Bin.) 99.05 (Multi.)
				UNSW-NB15		97.40 (Bin.) 84.98 (Multi.)
[41]	2020	Souza et al.	DNN, KNN	NSL-KDD	Binary	99.77
				CICIDS-2017		99.85
[42]	2020	Albahar et al.	ANN, Regularization	NSL-KDD	Multiclass	98.53
				UNSWNB15		94.58
				CIDDS-001		97.87
[43]	2020	Ahsan et al.	CNN, LSTM	NSL-KDD	Multiclass	99.70
[44]	2022	Banaamah et al.	CNN, LSTM, GRUs	Bot-IoT	Binary	99.80
[45]	2023	Kamalakkannan et al.	2D LSTM, CNN	NSL-KDD	Multiclass	98.00
[46]	2023	Shivhare et al.	CNN, LSTM, SVM	CICIDS-2017	Binary	97.29
[47]	2023	Qazi et al.	CNN, RNN	CICIDS-2018	Binary	98.90
[48]	2023	Xing et al.	CNN, Transformer	UNSW-NB15	Multiclass	88.47
[49]	2023	Xiang et al.	ML-CNN, BiLSTM, Transformer	UNSW-NB15	Binary	90.3
[50]	2023	Ullah et al.	Transformer, CNN, LSTM	UNSW-NB15, CICIDS-2017, NSL-KDD	Multiclass	99.21

2) Focused Data- and Algorithm-Level combination: Yan et al. [51] proposed a novel combinatorial IDS model based on a deep RNN and a region-adaptive SMOTE technique. This model significantly improved the detection rate of low-frequency attacks and overall efficiency while improving unknown attack detection. Al et al. [52] proposed a hybrid CNN + LSTM + SMOTE and the Tomek–Link sampling method (i.e., STL) to improve system performance to an impressive extent. Cao et al. [36] designed a CNN + GRU model that extracts spatiotemporal features from network data traffic. This model combines adaptive synthetic sampling (ADASYN) and repeatedly edits its nearest neighbors to process positive and negative sample imbalances in the original dataset. This model resolves both low classification accuracy and imbalance problems.

D. Motivation for and Purpose of this Study

Through the research and discussion of the above literature, we can see that model systems combining two or more algorithms can often obtain better detection capabilities than single algorithms. Of course, with that comes an increase in the cost of computation. Therefore, how to achieve better detection results at the exact computational cost, the reasonable choice of classification algorithm will be the key to the problem.

The CNN model has become one of the classification algorithms selected in this paper because it can comprehensively map the data features, mine the relationship between the features, and improve the accuracy of feature extraction. However, the CNN model focuses more on spatial local features and has time series characteristics for the traffic data studied in this paper. Therefore, the processing ability of sequence data will be emphasized in selecting the second classification algorithm. RNN, GRU, LSTM, and Transformer are all sequential models in deep learning. Compared with RNN and LSTM, the Transformer model can obtain the relationship between all the information in the sequence through the self-attention mechanism, which can better cope with the long-term dependency problem and has higher accuracy. The model can be operated in parallel, and the calculation speed is faster. Based on the above reasons, the CNN and the Transformer models have become the algorithm choices for this paper's hybrid intrusion detection system.

In addition, previous studies have primarily focused on the overall detection rate of the system, but for the typical unbalanced network traffic data, identifying a small number of attack samples is the key to detection classification. Therefore, the difference between this paper and previous studies is that the system focuses more on the identification rate of minority species without significantly affecting the overall detection rate. To achieve this goal, the system balances the sample size of the majority class and the minority class at the data level through data resampling technology to adapt to the common classifier that pursues global accuracy.

III. Proposed Model

The model proposed in this study uses the NSL-KDD and CICIDS2017 datasets as the research targets. New training, validation, and testing sets were divided by random sampling to digitize and normalize the original data. Most class samples were randomly undersampled to stress the sample imbalance problem.

The focus of this model is on the classification research of imbalanced data, which are divided into two levels for operation. First, at the data level, a data reconstruction strategy is used to adjust the internal distribution structure of the data so that the imbalanced dataset tends toward a balanced state. The measure is obtained by randomly undersampling the majority class samples in the training set and oversampling the minority class samples with SMOTE to achieve balanced data.

Second, at the algorithmic level, the model adjusts the traditional classification algorithm or proposes the optimization and improvement of existing classification ideas as an adaption technique to handle the inherent characteristics of imbalanced datasets, thereby improving the overall recognizability of the model. Research has shown that combined models consistently perform better than individual algorithms [38]. As mentioned, we combined the classic CNN with a transformer self-attention module to achieve optimization by combining multiple classifiers that adapt to the internal distributed structure of imbalanced datasets. Hence, the detection rate of the model will be improved.

This model accounts for both data- and algorithm-level aspects of the problem and utilizes their combined advantages to achieve superior recognition accuracy with minority class samples. Fig. 1 presents a schematic diagram of our proposed model.

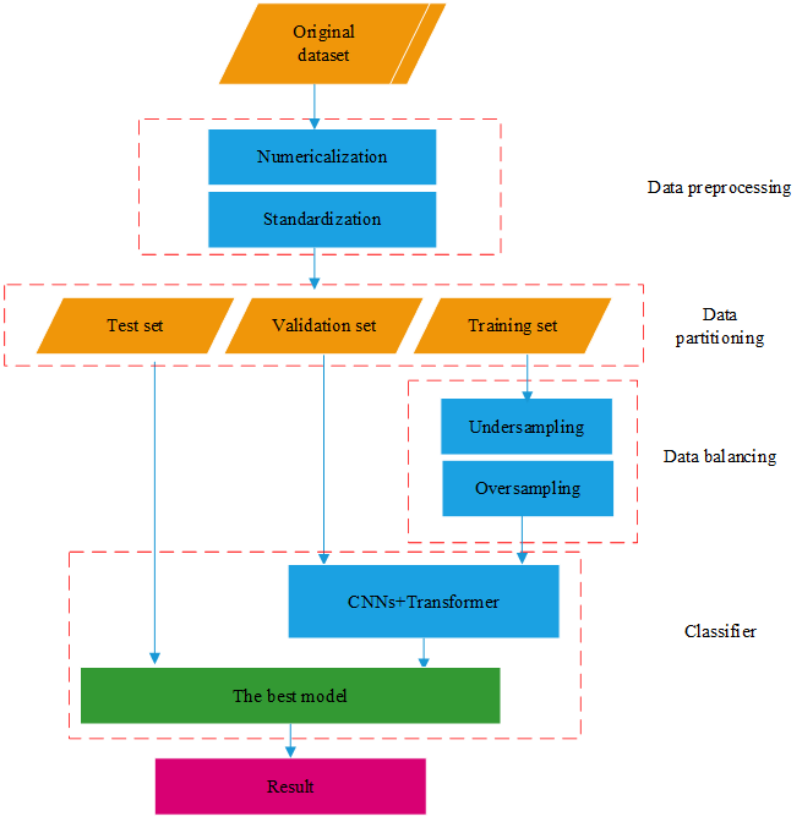


Fig. 1. Schematic diagram of the proposed model.

A. Dataset Description

1) NSL-KDD Dataset: According to [5], NSL-KDD [53] and KDD-CUP99 [54] are the most widely used datasets in IDS research (ca. 2012–2022). The NSL-KDD dataset was generated in 2009 and is commonly used to train models for anomaly detection. It is a revised version of the classic KDD99 dataset but retains its structure. The new dataset consists of four subsets: KDDTest+, KDDTrain+, KDDTest-21, and KDDTrain+_20%, where the latter two are subsets of the first two, respectively.

In the NSL-KDD dataset, each sample record contains 41 attribute features and a classification identifier. Normal and abnormal network connections are marked with the classification identifier. The normal type is represented as "normal," and the dataset contains many anomalies and 39 attack identifiers. These identifiers are divided into four categories by type: denial of service (DoS), probe, root-to-local (R2L), and unauthorized-to-root (U2R).

Our experiment uses the original data sources of KDDTrain+ (125,973 sample records) and KDDTest+ (22,544 sample records). Table II presents the sample size distributions of each attack type.

2) CICIDS2017 Dataset: Table II shows that the NSL-KDD dataset is a typical imbalanced dataset. Notice the small proportion of Probe, R2L, and U2R attack-type samples, especially for U2R attacks. Although this dataset is very popular in IDS studies, some researchers have pointed out that it is somewhat outdated.

Emerging datasets include UNSW-NB15, CICIDS2017, Bot-IoT, and others. Among them, CICIDS2017 is the most popular. Therefore, we chose CICIDS2017 as our second benchmark to gauge performance differences.

The CICIDS2017 dataset was released in 2017 [55], providing normal data and the latest common attack types, similar to real-world data. It contains 2,830,743 network traffic samples, each containing 83 network traffic features. It also includes one benign and 14 attack categories, including the standard DoS, botnet, web, infiltration, file transfer protocol patator, and SSH patator types [56]. Among the 14 attack categories, tags with similar features and behaviors are merged to form five new categories. The distribution of the number of samples in the CICIDS2017 dataset is shown in Table III. The CICIDS2017 dataset is also imbalanced, with bot-and-web attack class samples being particularly scarce.

TABLE II. DISTRIBUTION OF VARIOUS SAMPLES FROM THE NSL-KDD DATASET

Dataset	The number and proportion of various types of samples					
	Total	***Normal***	***DoS***	***Probe***	***R2L***	***U2R***
KDD Train+	125973	67343 (53.46%)	45927 (36.46%)	11656 (9.25 %)	995 (0.79 %)	52 (0.04%)
KDD Test+	22544	9711 (43.08%)	7458 (33.08%)	2421 (10.74%)	2754 (12.22 %)	200 (0.89%)

TABLE III. DISTRIBUTION OF VARIOUS SAMPLES IN THE CICIDS2017 DATASET

Dataset	Number and proportion of various types of samples					
	BENIGN	***Bot***	***BruteForce***	***DoS /DDoS***	***Port Scan***	***Web Attack***
CICIDS2017	2035505 (83.91 %)	1943 (0.08 %)	8551 (0.35%)	320269 (13.20 %)	57341 (2.36 %)	2118 (0.09 %)

B. Data Preprocessing

Using the NSL-KDD dataset as an example, data preprocessing was introduced, and the operation of the CICIDS2017 dataset was similarly manipulated.

1) Numericalization: The NSL-KDD dataset contains 41 attribute features (i.e., 38 digital and three non-digital types). Because the input value of the model should be a digital matrix, it was necessary to use a numerical method to map data with symbolic features into digital feature vectors. We used the LabelEncoder method of the preprocessing module in the sklearn library to convert the three non-digital features (i.e., protocol_type, service, and flag) into digital features.

2) Standardization: Unlike normalization, which is easily affected by outliers, standardization is relatively stable; thus, it is suitable for noisy big data scenarios. Therefore, standardization was used for data preprocessing. The original data were transformed into a range with a mean of zero and a standard deviation of one so that the processed data would conform to a standard normal distribution. The StandardScaler method of the preprocessing module in the sklearn library uses a standard z-score scaling calculation formula, expressed using Eq. (1):

$$X' = \frac{\chi - mean}{\sigma}, \quad (1)$$

where, X' represents the converted data value, χ is the original data value, mean is the mean value of the column data, and σ is the standard deviation of the column data.

C. Dataset Partitioning

The KDDTrain+ and KDDTest+ subsets of the NSL-KDD dataset were used as the original data, and new training, validation, and testing sets were formed by random sampling. It lists the number and proportions of each sample set after division. The CICIDS2017 dataset was also divided according to the same ratio, and the numbers after the division are listed in Table IV. To achieve good data balance, undersampling and oversampling were performed on the training set samples.

TABLE IV. NUMBER AND PROPORTION OF DATASETS AFTER PARTITIONING

Dataset	#training set	#validation set	#testing set
NSL-KDD	103,961	14,852	29,704
CICIDS2017	1,698,008	242,573	485,146
Proportion	70%	10%	20%

D. Data Balancing

1) Undersampling: The undersampling method achieves data equalization by randomly removing a certain proportion of majority instances from the RUS dataset [23]. This process consists of the following steps:

a) The numbers of majority samples, N1, and minority samples, N2, are calculated.

b) Based on the set sampling ratio, r, we calculate the number of majority class samples needing deletion (N1 - N2 * r).

c) Randomly selected samples from the majority class, S_{maj}, to form the sample set E; remove sample set E from S_{maj}; generate a new dataset $S_{new-maj} = S_{maj} - E$.

In the NSL-KDD dataset, NORMAL and DoS samples belong to the majority class, and undersampling was performed using RUS samples. The BENIGN and DoS/DDoS samples of the CICIDS2017 dataset belong to the majority class and are undersampled.

2) Oversampling: Oversampling is used to rebalance a dataset by creating fake minority instances, and SMOTE [22] is the best method [57] in our case as it effectively compensates for the shortcomings of random oversampling and is superior to simple replication, which can easily cause model overfitting and weaken generalizability. SMOTE also has the advantages of a simple design and strong robustness. Moreover, it uses interpolation between minority class samples and their nearest neighbors to generate new synthetic samples [58]. The SMOTE steps are as follows:

a) For each sample X in the minority class, a k-NN is used to sample each minority class sample.

b) We determine the sampling rate, N, based on the sample imbalance ratio and randomly select N samples from K nearest neighbors for random linear interpolations.

c) We construct a new minority class sample using Eq. (2):

$$\mathrm{New} = \mathrm{x_i} + rand(0,1) \times \left(\mathrm{y_j} - \mathrm{x_i}\right), \mathrm{j} = 1, 2, \ldots \mathrm{N} \quad , \tag{2}$$

where, $\mathrm{x_i}$ is an observation point in the minority class, $\mathrm{y_j}$ is a randomly selected K -nearest neighbor, and $rand(0,1)$ represents a random number generated between zero and one.

d) New samples are combined with the original data to form a new dataset.

In the NSL-KDD dataset, Probe, R2L, and U2R samples belong to a minority class and were oversampled with SMOTE to increase the number of class samples. For the CICIDS2017 dataset, the Bot, Brute Force, PortScan, and Web Attack samples belong to the minority class and were oversampled. The training set samples were balanced at the data level via undersampling and oversampling.

E. Model Structure

1) CNN: CNNs are feedforward neural networks with convolution calculations and a deep structure that extract features accurately and efficiently [59]. The error function is obtained by calculating the difference between the actual and predicted values. Network parameters are adjusted retroactively until the model reaches an optimal solution [60]. This method has been widely used in several fields, such as NLP and computer vision.

A CNN generally comprises a convolution layer, activation function, pooling layer, and a fully connected layer [61] as shown in Fig. 2. The convolution layer extracts high-level features from the input data, and the pooling layer performs feature selection and information filtering on the graph data output by the convolution layer, thereby reducing the amount of data processing.

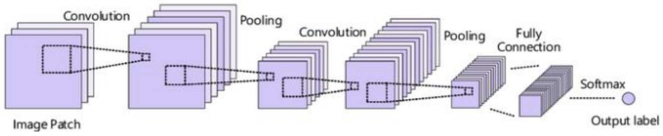


Fig. 2. CNN structure.

2) Transformer: A transformer is a deep learning model [33] that is widely used for NLP and other sequential data processing tasks.

The transformer differs from traditional RNNs and CNNs in that they adopt a novel self-attention mechanism that allows the model to assign different weights to different elements when processing input sequences. It calculates the similarity score between elements and uses the score to calculate the weighted averages of relationships among elements. Notably, the transformer supports parallel computing, this allows it to handle long sequences easily without step-by-step iterations. The self-attention mechanism also allows the transformer to incorporate information from the entire sequence into its calculations, which leads to better long-range dependencies.

CNNs are particularly adept at modeling fine-grained local features due to their convolutional operations and hierarchical structure. Nevertheless, their global modeling ability is weak, whereas the transformer excels at modeling global contextual information [62]. The proposed framework utilizes complementary CNN characteristics to extract local, spatial, and time series features.

3) Hybrid model: This article adopts a hybrid architecture that combines the CNN and the transformer as illustrated in Fig. 3. Spatial features are extracted after preprocessing and sample balancing in one-dimensional (1D) convolutional and pooling layers. Then, by using the self-attention mechanism of the transformer to process the data, the shortcomings of the RNN's short-term memory and the CNN's difficulties in learning remote dependencies are overcome, and temporal and global features are extracted. Finally, using flattening and fully connected functions, the data are classified according to attack type. For the NSL-KDD dataset, the data were divided into five categories: one normal and four attack. The CICIDS2017 dataset was divided into six categories: one benign and five attacks.

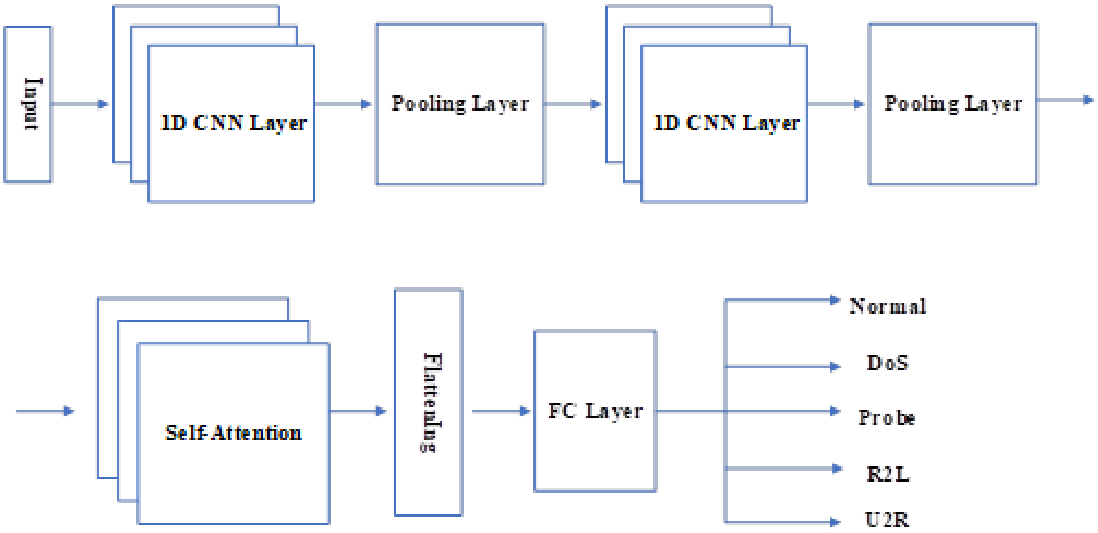


Fig. 3. Hybrid CNN–Transformer architecture.

IV. Experimental Results and Discussion

A. Evaluation Indicators

Commonly used evaluation indicators for classification problems are accuracy (ACC), precision (PRE), recall (i.e., TPR), false-positive rate (FPR), and F1-measure. It is necessary to adopt reasonable evaluation criteria for unbalanced data, including the F1-measure, G-mean, receiver operating characteristic (ROC) curve, and area under the ROC curve (AUC) values.

Accuracy is defined by Eq. (3), which reflects the percentage of correctly predicted samples among the total number of predicted samples:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}. \quad (3)$$

Precision is the ratio of correctly predicted positive samples to the total number of positive samples, as shown in Eq. (4):

$$\text{Precision} = \frac{TP}{TP+FP}. \quad (4)$$

Recall describes the ratio of the number of correctly predicted positive samples to the total number of positive samples as formulated in Eq. (5):

$$\text{Recall} = \frac{TP}{TP+FN}. \quad (5)$$

FPR is the number of false positive samples detected divided by the total number of TN samples, as defined by Eq. (6):

$$FPR = \frac{FP}{FP+TN}. \quad (6)$$

The F1-measure is a comprehensive assessment of precision and recall and represents the harmonic average between them, as defined by Eq. (7):

$$\text{F1-Measure} = 2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} = \frac{2TP}{2TP+FP+FN} \quad (7)$$

The G-mean is a standard that comprehensively considers both recall and accuracy. A high G-mean value indicates good modularity, reflecting the geometric mean of sensitivity (i.e., hit rate or recall) and precision. The G-mean is defined in Eq. (8):

$$G-\text{Mean} = \sqrt{\frac{TP}{TP+FN}\times\frac{TN}{TN+FP}}. \quad (8)$$

The ROC curve defines TPR and FPR in terms of horizontal and vertical coordinates, respectively. Each threshold corresponds to a point (FPR, TPR), and all points are connected as the threshold changes.

Although the ROC curve can comprehensively and intuitively express the performance of a classifier, it cannot provide a specific value. Therefore, it is usually evaluated using the area AUC, as defined in Eq. (9):

$$AUC = \frac{TP \times FP + 2TP \times TN + FN \times TN}{2(TP + FN) \times (FP + TN)} . \qquad (9)$$

AUC values range from zero to one; the larger the AUC, the better the classification performance.

B. Experimental Results

The experiment was conducted on a desktop Intel 3.10 GHz processor with 64-GB memory, no GPU acceleration, and a 64-bit Windows 11 operating system. The programming tool was Keras 2.9.0, based on TensorFlow. The NSL-KDD and CICIDS 2017 datasets were used to train the model shown in Fig. 1. For the NSL-KDD dataset, owing to the small amount of data, the batch size was set to 256, and the training epochs were set to 200. The CICIDS2017 dataset contains a considerable amount of data. To accelerate the convergence speed of the model, the batch size was set to 512, and 40 epochs of training were performed. Finally, the model parameters with the best effects on the corresponding datasets were obtained. Subsequently, the model with the optimal parameters was tested on the testing set to obtain classification results, and the confusion matrix was constructed as shown in Fig. 4 and Fig. 5.

Multiple classification experiments were conducted for different attack categories. The NSL-KDD dataset included normal, DoS, Probe, U2R, and R2L classes. The CICIDS 2017 dataset consisted of BENIGN and five attack classes: bot, brute-force, DoS/DDoS, PortScan, and web types. The experimental results are presented in Tables V and VI, respectively. For most class samples, the classification performance of the model was good. For the minority class samples, the model's classification performance decreased to some extent; however, the degree of decrease was not significant. The model does not sacrifice the classification performance of other categories to improve the classification accuracy of any specific category. Therefore, the overall classification performance of the model is very well-balanced.

The overall classification results of the model are presented in Table VII. Although the overall accuracy was not very high, the model did not sacrifice the classification effects of a few classes in exchange for higher overall accuracy, which is a unique demonstration of superior classification procedures. Therefore, the model showed little difference in the classification effects between the majority and minority classes. Moreover, it tended to improve the recognition rate of minority classes (e.g., U2R and R2L) in the NSL-KDD dataset and Bot and Web classes in the CICIDS2017 Dataset).

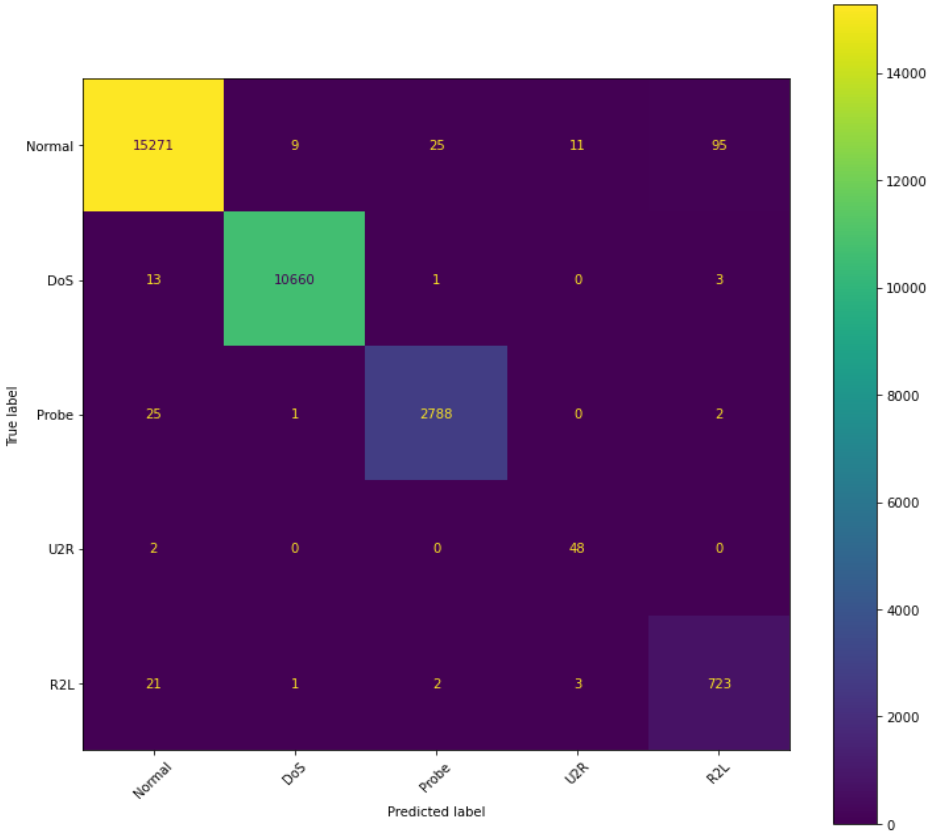


Fig. 4. Confusion matrix of classification results of the NSL-KDD dataset.

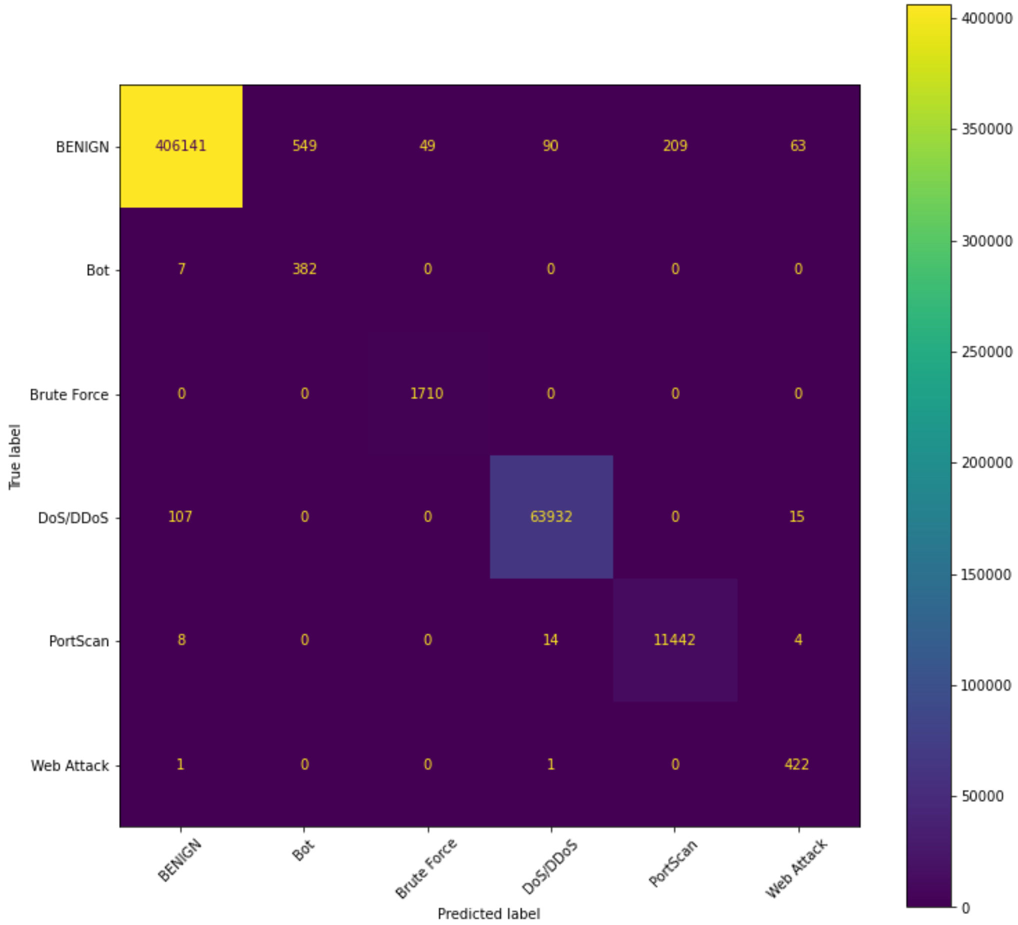


Fig. 5. Confusion matrix of classification results of the CICIDS2017 dataset.

TABLE V. FIVE CLASSIFICATION RESULTS FOR THE NSL-KDD DATASET

Type	Accuracy (%)	Precision (%)	Recall (%)	FPR (%)	F1 (%)	G-mean (%)	AUC
Normal	99.32	99.60	99.09	0.43	99.35	99.33	99.97
DOS	99.91	99.90	99.84	0.06	99.87	99.89	99.99
Probe	99.81	99.01	99.01	0.10	99.01	99.45	99.98
U2R	99.95	77.42	96.00	0.05	85.71	98.01	99.95
R2L	99.57	87.85	96.40	0.35	91.93	97.96	99.77

TABLE VI. SIX CLASSIFICATION RESULTS FOR THE CICIDS2017 DATASET

Type	Accuracy (%)	Precision (%)	Recall (%)	FPR (%)	F1 (%)	G-mean (%)	AUC
BENIGN	99.78	99.97	99.76	0.16	99.87	99.80	99.99
Bot	99.89	41.03	98.20	0.11	57.88	99.04	99.89
Brute Force	99.99	97.21	100.00	0.01	98.59	99.99	1.00
DoS / DDoS	99.95	99.84	99.81	0.02	99.82	99.89	1.00
PortScan	99.95	98.21	99.77	0.04	98.98	99.86	99.99
Web Attack	99.98	83.73	99.53	0.02	90.95	99.76	1.00

TABLE VII. MODEL CLASSIFICATION RESULTS

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)
NSL-KDD	99.28	92.75	98.07	95.17
CICIDS 2017	99.77	86.66	99.51	91.01

C. Analysis and Discussion

1) Impact of model structure on results: In this section, the structure of the proposed model is discussed. We compared the classification effects of the model before and after data balancing and the single-network model with the hybrid model of both. The following conclusions were drawn from the NSL-KDD dataset, as listed in Table VIII.

The overall effect of the model after data balancing was better than that of the model without data balancing. Moreover, the impact of the hybrid model was better than that of the single-network model.

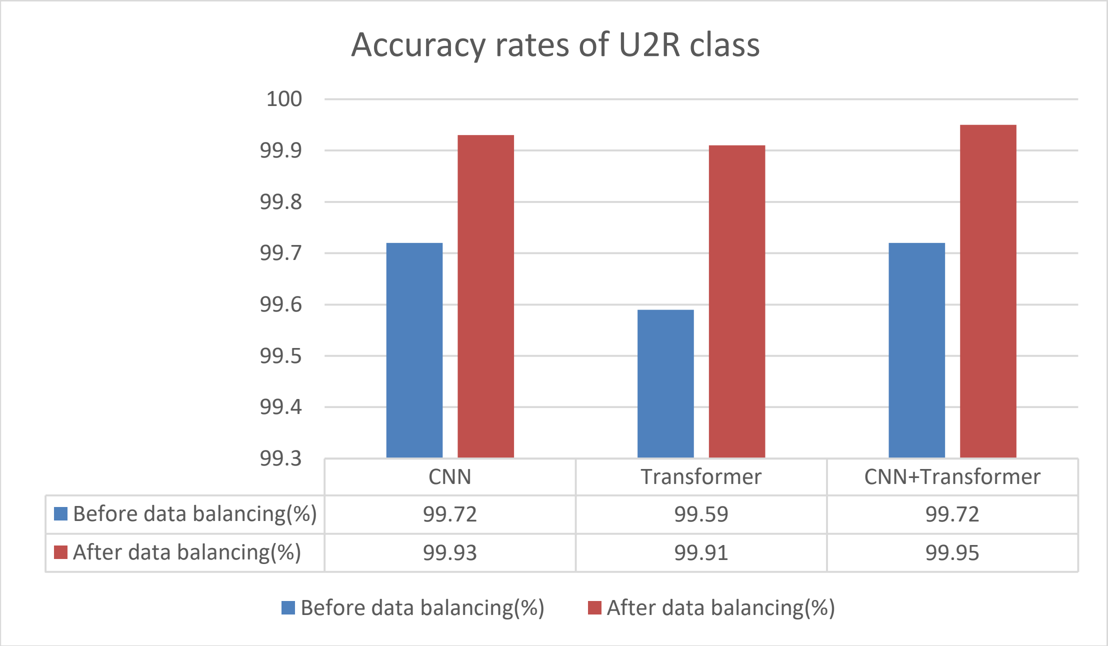
At the same time, data balancing is beneficial for improving the classification effect of minority classes. Fig. 6 and Fig. 7 show the comparison of precision before and after data balancing for the minority classes U2R and R2L, respectively. From the figures, we can see that regardless of whether it is a single algorithm model or a hybrid model, the classification accuracy after data balancing has increased to varying degrees. This also confirms the necessity of data balancing operations.

Similar conclusions were drawn for the CICIDS2017 dataset. The effect of the hybrid model was better than that of the single network model. Data balancing provided better improvements to accuracy and precision indicators, as shown in Table IX.

Fig. 8 and Fig. 9 present a comparative analysis of the precision of rare classes—Bot and Web Attack—in the CICIDS2017 dataset, both before and after the application of data balancing techniques. Similar to the NSL-KDD dataset, the conclusion drawn from these figures is that data balancing is beneficial for improving the classification accuracy of minority classes.

TABLE VIII. COMPARISON OF THE RESULTS OF THE NSL-KDD DATASET UNDER DIFFERENT MODEL CONFIGURATIONS

	Before data balancing			After data balancing		
Model	***CNN***	***Transformer***	***CNN+Transformer***	***CNN***	***Transformer***	***CNN+Transformer***
Accuracy (%)	98.47	98.41	98.56	99.24	98.81	99.22
Precision (%)	82.36	80.82	82.62	91.94	86.18	91.68
Recall (%)	97.98	97.47	98.07	98.04	97.82	98.19
F-Measure (%)	87.31	85.35	87.51	94.64	90.47	94.56



	CNN	Transformer	CNN+Transformer
🟦 Before data balancing(%)	99.72	99.59	99.72
🟥 After data balancing(%)	99.93	99.91	99.95

Fig. 6. Comparison of the U2R class accuracy rate before and after data balancing.

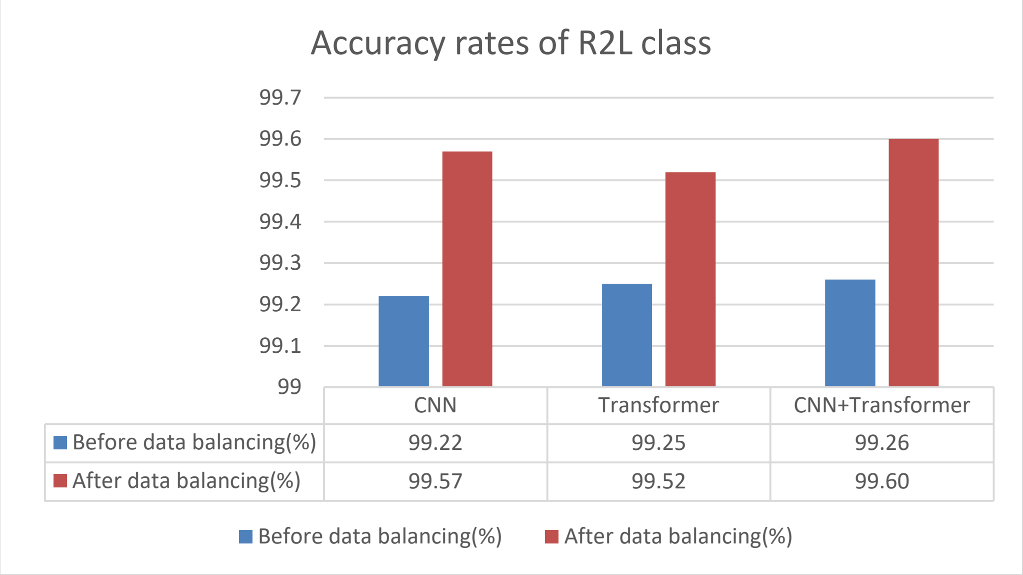


Fig. 7. Comparison of the R2L class accuracy rate before and after data balancing.

TABLE IX. COMPARISON OF THE RESULTS OF THE CICIDS2017 DATASET UNDER DIFFERENT MODEL CONFIGURATIONS

Model	Before data balancing			After data balancing		
	CNN	***Transformer***	***CNN+Transformer***	***CNN***	***Transformer***	***CNN+Transformer***
Accuracy (%)	98.55	97.15	98.36	99.73	98.24	99.77
Precision (%)	69.38	67.12	71.24	85.84	69.53	86.66
Recall (%)	99.34	98.14	99.52	99.55	99.16	99.51
F-Measure (%)	73.21	69.34	75.15	90.26	72.52	91.01

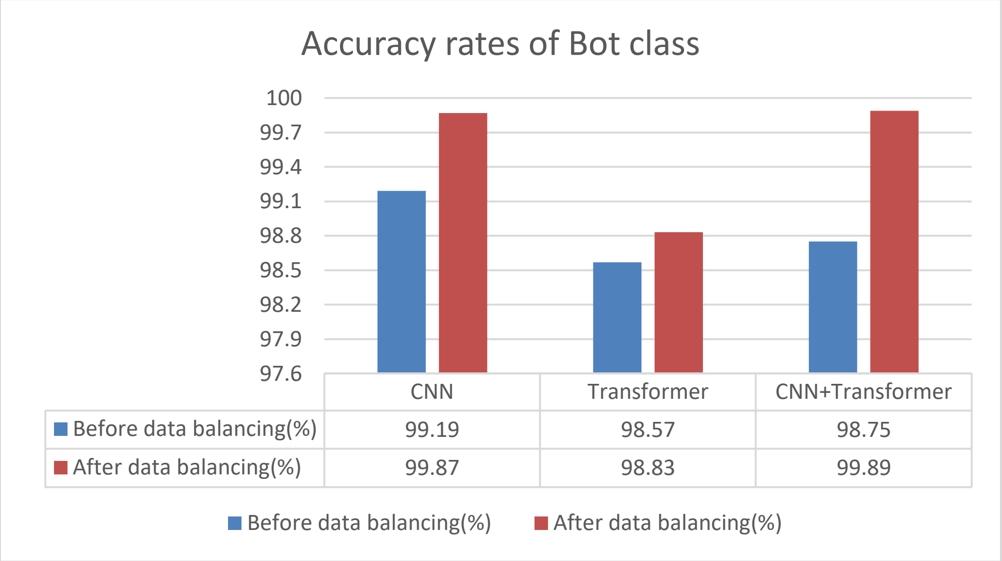
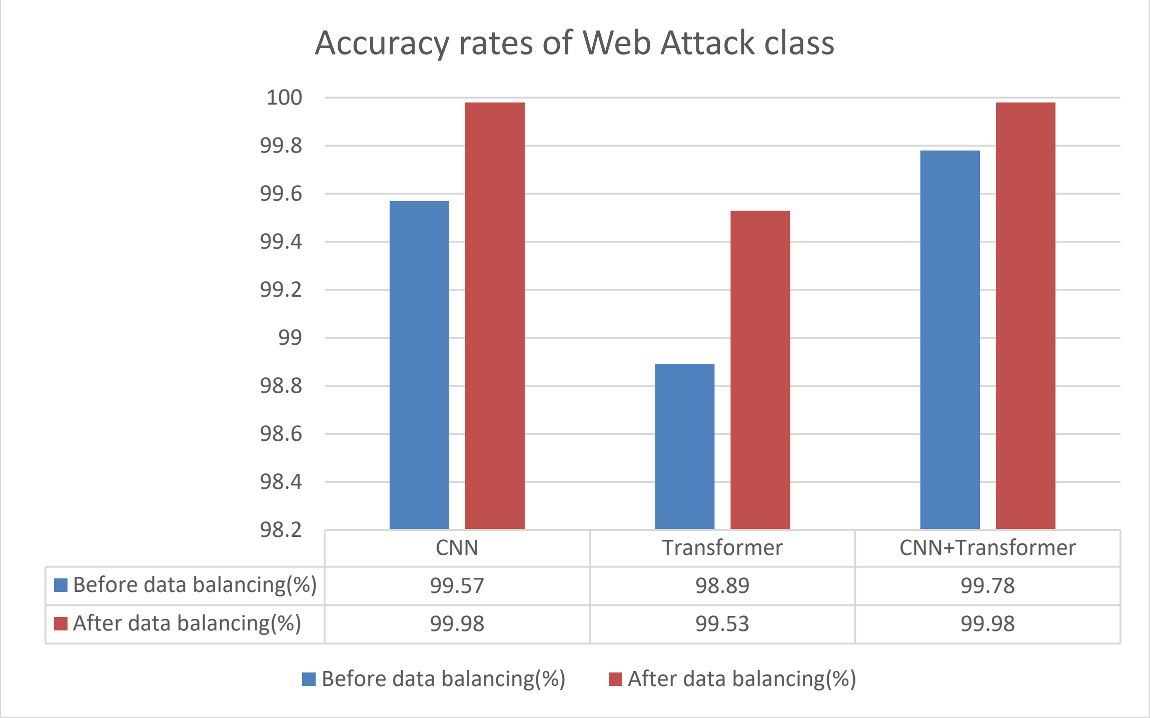


Fig. 8. Comparison of Bot class accuracy rates before and after data balancing.



	CNN	Transformer	CNN+Transformer
🟦 Before data balancing(%)	99.57	98.89	99.78
🟥 After data balancing(%)	99.98	99.53	99.98

Fig. 9. Comparison of Web Attack class accuracy rate before and after data balancing.

2) Impact of sampling rate on results: The previous section showed that data balancing benefits minority class detection. In this section, we focus on comparing the different sampling rates of rare classes to explore the impact of sampling rates. For the NSL-KDD dataset, we checked the U2R category. In contrast, for the CICIDS2017 dataset, we checked the Bot and Web Attack categories due to their low representation. During model training, 100, 300, 500, and 1,000% samples were considered for the given categories, and the optimal model parameters generated were predicted using the testing set. The experimental results are presented in Tables X to XII.

TABLE X. COMPARISON OF RESULTS FOR THE U2R CATEGORY UNDER DIFFERENT SAMPLING RATES

Sampling rate (%)	**Recall (%)**	**Accuracy (%)**	**F-Measure (%)**	**G-mean (%)**
100	70.00	99.93	76.09	83.66
300	72.00	99.92	75.79	84.84
500	74.00	99.91	74.00	86.00

TABLE XI. COMPARISON OF RESULTS FOR THE BOT CATEGORY UNDER DIFFERENT SAMPLING RATES

Sampling rate (%)	**Recall (%)**	**Accuracy (%)**	**F-Measure (%)**	**G-mean (%)**
100	32.65	99.95	52.24	57.14
300	61.44	99.94	62.41	78.37
500	94.34	99.93	67.82	97.09
1000	94.86	99.93	69.82	97.19

TABLE XII. COMPARISON OF RESULTS FOR THE WEB ATTACK CATEGORY UNDER DIFFERENT SAMPLING RATES

Sampling rate (%)	**Recall (%)**	**Accuracy (%)**	**F-Measure (%)**	**G-mean (%)**
100	82.08	99.99	96.43	90.59
300	95.52	99.99	96.36	97.72
500	97.41	99.99	95.10	98.67
1000	97.64	99.99	94.49	98.80

These results show that increasing the sampling rate significantly improved the recall rate, F-measure, and G-mean for rare categories. However, this had little impact on overall classification accuracy. Due to the small proportions of rare classes in the original dataset, it was difficult for the model to train effectively for class recognition. Therefore, increasing the sampling rate is equivalent to increasing the training opportunities of the model for that category, thereby improving the recall of subsequent testing data. Thus, improving the detection rate for minority classes comes at the cost of increasing training time.

D. Comparisons of Experimental Results

We compared the above experimental results with methods from the relevant literature to verify our model's effectiveness with multiclassification problems using unbalanced data. We first compared NSL-KDD data, as the related literature is abundant.

First, the classification accuracy of multiple classifications was compared, as presented in Table XIII. Our model had the highest classification accuracy for all five categories, and there were no cases in which the accuracy of a specific category was particularly low. Again, the accuracy of a few categories was not sacrificed in exchange for higher overall accuracy.

TABLE XIII. ACCURACY COMPARISONS OF FIVE CLASSIFICATIONS

References	Normal (%)	DOS (%)	Probe (%)	U2R (%)	R2L (%)
Zhang-2019- [39]	-	99.45	99.37	98.68	97.78
Ahsan-2020- [43]	98.5	98.8	0	99.4	94.6
LIU-2023- [63]	97.7	94.6	94.7	0.3	0.4
Proposed model	99.32	99.91	99.81	99.95	99.57

Next, multi-classification recall rates were compared, and the results are listed in Table XIV. It can be seen from the table that the recall rates of the DOS and R2L categories were the highest compared with those reported in the relevant literature. The difference between the other three categories and the highest values in the literature was insignificant.

TABLE XIV. RECALL COMPARISONS OF FIVE CLASSIFICATIONS

References	Normal (%)	DOS (%)	Probe (%)	U2R (%)	R2L (%)
Zhang-2019- [39]	-	99.7	99.4	98.2	93.4
Albahar-2020- [42]	98	97.8	95.6	96.9	92.4
Ahsan-2020- [43]	98.5	98.8	0	99.4	94.6
Onah-2021- [64]	97.5	96.9	93.4	73.5	77.1
LIU-2023- [63]	97.7	94.6	94.7	0	0
Kamalakkannan-2023- [45]	99.57	99.76	99.15	25	88.41
Proposed model	99.09	99.84	99.01	96	96.40

The classification FPRs of multiple classifications were then compared, as shown in Table XV. It can be seen that, apart from a few R2L cases, the FPR of our model was the lowest of all.

TABLE XV. FPR COMPARISONS OF FIVE CLASSIFICATIONS

References	Normal (%)	DOS (%)	Probe (%)	U2R (%)	R2L (%)
Zhang-2019- [39]	-	0.8	0.7	1.8	7.3
Albahar-2020- [42]	0.73	0.54	0.67	0.33	0.87
Ahsan-2020- [43]	1.5	1.2	1	0.6	5.4
Onah-2021- [64]	0.6	0.6	0.4	0.2	0.1
Proposed model	0.43	0.06	0.10	0.05	0.35

Finally, for imbalanced data classification problems, the F1 measure is often more important than other metrics. Table XVI presents the results of the multicategory F1-measure comparisons. Apart from the U2R category, the F1 measure of our model was the best.

TABLE XVI. F1-MEASURE COMPARISON OF FIVE CLASSIFICATIONS

References	Normal (%)	DOS (%)	Probe (%)	U2R (%)	R2L (%)
Albahar-2020- [42]	98.5	98.3	94.8	97.3	66.5
Ahsan-2020- [43]	99.1	98.3	0	99.2	85.4
LIU-2023- [63]	98.9	97.2	97.3	0.5	0.7
Proposed model	99.35	99.87	99.01	85.71	91.93

Using the CICIDS2017 dataset, our model also showed advantages in accuracy and recall, as shown in Table XVII.

TABLE XVII. COMPARISON OF THE RESULTS OF THE CICIDS2017 DATASET

References	Accuracy (%)	Recall (%)
Abdel-Basset-2021- [65]	99.69	96.29
Khan-2021- [66]	98.76	98.69
Chen-2022- [67]	99.73	79.13
Wu-2022- [68]	99.35	98.83
Proposed model	99.77	99.51

Through the above comparative analyses, our hybrid model, based on data balancing and two deep learning networks, has clear advantages and achieved excellent results in multiclassification problems with unbalanced data.

V. CONCLUSIONS AND FUTURE RECOMMENDATIONS

NIDS plays vital network security roles in identifying, preventing, and countering network threats. Owing to the large amount of unbalanced data collected in network datasets, FPs and omissions significantly reduce the detection efficiency of extant IDSs. This paper proposed a deep learning model that combines data balancing and a CNN + Transformer hybrid to improve the data distribution of the original dataset via undersampling and oversampling techniques. Our data redistribution method increases the likelihood of identifying minority classes based on model training, and the experimental results show that our innovations effectively improve this detection rate. Our hybrid model’s algorithm-level improvements increased recognition training based on fused spatiotemporal features, and the experimental results show that the proposed system, combined with multiple combined processes, identifies anomalies more efficiently and accurately than any single network model.

For the classic NSL-KDD and modern CICIDS2017 datasets, our model was more effective in multiclassification data applications and was superior to existing IDS models in terms of accuracy, FPR, F1-mean, and other indicators. Notably, the CICIDS2017 dataset showed superiority in training compared with existing models in terms of accuracy and recall.

Although the model proposed in this paper has advantages over existing systems, several other data balancing activities, such as the edited nearest neighbor, Tomek–Links, SMOTEBoost, and ADASYN methods described, should be tested. Many LSTM, GRU, DBN, and other variants should also be tested. The objective is to improve the detection effects of data classifications based on innovative model structures so that network security professionals and scholars can obtain better IDS results, even in the face of scarce data.

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Addressing Imbalanced Data in Network Intrusion Detection: A Review and Survey

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***Abstract*—The proliferation of internet-connected devices, including smartphones, smartwatches, and computers, has led to an unprecedented surge in data generation. The rapid rise in device connectivity points to an urgent need for robust cybersecurity measures to counter the mounting wave of cyber threats. Among the strategies aimed at establishing efficient network intrusion detection systems, the integration of machine learning techniques is a prominent avenue. However, the application of machine learning models to imbalanced intrusion detection datasets, such as NSL-KDD, CICIDS2017, and UGR'16, presents challenges. In such intricate scenarios, accurately distinguishing network intrusions poses a formidable challenge. The term "imbalance" refers to the imbalanced distribution of data across classes, which adversely affects the precision of machine learning algorithm classifications. This comprehensive survey embarks on a thorough exploration of the spectrum of methodologies proposed to address the challenge of imbalanced data. Simultaneously, it assesses the efficacy of these methodologies within the realm of network intrusion detection. Moreover, by shedding light on the potential consequences of not effectively tackling imbalanced data, this study aims to provide a holistic understanding of the intricate interplay between machine learning and intrusion detection in imbalanced settings.**

Keywords*—Network intrusion detection system; data imbalance; resampling; data level techniques; hybrid techniques

I. Introduction

In parallel with technological advancements and the proliferation of networks, vulnerabilities to diverse attacks have emerged, potentially leading to system damage, network disruptions, data loss, or unauthorized access. The escalation of network intrusions has become a pressing concern, impacting governments, businesses, and essential infrastructure. Network intrusion detection systems (NIDS) have come to the fore as a means of addressing these challenges. These systems employ advanced algorithms to navigate intricate and extensive data landscapes, functioning as vigilant software that enhances the monitoring of network activities. Their primary mission is to identify and categorize attacks [1].

It has become clear in recent times that the ability to identify attack patterns is crucial given the continuous evolution and increasing sophistication of cyber threats. A report by firewall maker SonicWall shows a significant increase in ransomware attacks of 105% in 2021 compared to the previous year. Additionally, there were a staggering 5.4 billion malware attacks in 2022 [2]. Artificial intelligence (AI) has a central role in addressing this pressing issue, leveraging machine learning and deep learning techniques to construct intelligent NIDS. The remarkable capabilities offered by machine learning enable meticulous analysis of vast volumes of network traffic data, tackling intricate classification challenges and automating decision-making processes.

Over the last decade, researchers have introduced a myriad of machine learning and deep learning-based solutions aimed at enhancing the efficacy of NIDS, pinpointing malicious attacks [3] [4] [5]. The architecture of the machine learning network is a core feature of this complex process. This framework encompasses several key stages: data preprocessing to ensure readiness for data analysis, feature selection to identify relevant variables, model selection to determine the optimal algorithm, training to absorb data patterns, evaluation to assess model performance, and prediction to apply trained models to new data, generating actionable outcomes. This framework is visually depicted in Fig. 3.

However, machine learning and deep learning algorithms often face the challenge of imbalanced class distributions, with certain classes significantly more prevalent than others. This imbalance poses a formidable hurdle as learning algorithms tend to gravitate toward the majority class, impacting the accuracy of classification, particularly for specific intrusion types. Several applications, for example, energy forecasting and climate data analysis [6], operate in nonstationary environments. In other words, the process of generating data is changing over time. Branco et al. [7] undertook a negative impact test of class imbalance on classifiers like decision trees, neural networks, and k-nearest neighbor. It is argued that imbalanced domains are caused by a mismatch between the importance assigned by the user to some predictions and the representativeness of those values when they are applied to the available sample data. This misclassification can have dire consequences, necessitating further investigations into intrusions if normal behavior classes are inaccurately categorized. Moreover, inaccurate intrusion categorization has the potential to inflict harm upon systems [8].

From the vantage point of data mining, the minority class often carries heightened significance. To address biases stemming from imbalanced data scenarios, it is essential to create intelligent systems, which constitute the field of "learning from imbalanced data". The essence of the class imbalance problem is often distilled into a ratio reflecting total occurrences in minority classes relative to their majority counterparts. Imbalanced data embody traits such as overlap, minimal distinct density, noisy data, and dataset variance, collectively posing substantial challenges to effective categorization.

Recently, an array of cutting-edge learning techniques has emerged, tailored to confronting classification issues embedded within imbalanced datasets [9]. Navigating the reconciliation of class imbalance is closely intertwined with addressing overlap, consistent with the overarching objective of establishing decisive boundaries between classes and facilitating clear differentiation across the spectrum of learning models [10]. This ensemble of techniques enhances accuracy across various strata, spanning inconspicuous elements and random sampling, all without necessitating replacement.

The main objective of this study is to review scientific papers addressing the problem of imbalanced data in the field of NIDS and analyze the methods used to tackle this issue. The analysis showed that oversampling techniques, such as the Synthetic Minority Over-Sampling Technique (SMOTE) and the Adaptive Synthetic (ADASYN) sampling approach, are commonly used to balance datasets.

The remainder of the paper is structured as follows: Section II outlines the survey methodology, Section III presents a comprehensive overview of the datasets, Section IV examines the prevalent techniques employed to address imbalanced data, and finally, Section V provides concluding reflections and highlights potential avenues for future research.

II. Survey Methodology

To conduct the survey concerning imbalanced data within intrusion detection datasets, the study undertook a meticulous analysis of scholarly articles sourced from esteemed publishers of research literature, namely Elsevier, Springer, MDPI, and IEEE. A two-fold approach was employed to select the most pertinent papers. First, we searched specific keywords associated with unbalanced data, such as "class imbalance" and "intrusion detection system", to pinpoint papers likely to address the subject matter. In the second phase, we conducted a meticulous assessment to exclude scientific papers that did not originate from reputable academic journals. This stringent process guaranteed the inclusion of papers that adhered to rigorous academic standards and were founded on robust research methodologies. By applying these dual steps, we identified and curated research papers that offered valuable insights into the intricacies of imbalanced data within intrusion detection datasets.

The holistic workflow of these techniques to address imbalance is succinctly portrayed in Fig. 1.

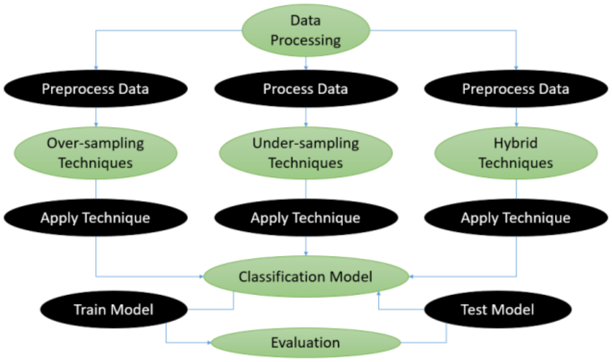

Fig. 1. Flow of imbalance technique approaches.

III. Data Description

Intrusion detection datasets exhibit variations in terms of release dates, sizes, attack classifications, and data collection methods. This section offers a comprehensive overview of prominent datasets utilized in intrusion detection research, providing insights into their key attributes and significance.

A. CICIDS2017

The CICIDS2017 dataset, delivered in 2017, is a significant asset containing roughly 2.8 million records with 83 features. It remains as a demonstration of the developing idea of digital dangers, embodying fourteen unmistakable assault types going from customary Forswearing of Administration (DoS) assaults to additional refined methods like Cross-Site Prearranging (XSS). The expansiveness and profundity of this dataset make it an important resource for concentrating on the complexities of organization intrusion detection [11].

B. CSE-CIC-IDS2018

Presented in 2018 by the Canadian Organization for Network safety (CIC) and Correspondences Security Foundation (CSE), the CSE-CIC-IDS2018 dataset addresses a huge progression in intrusion detection research. With roughly 16.2 million records and 80 features, this dataset gives a rich wellspring of information for examining different sorts of intrusion assaults, including Conveyed Refusal of Administration (DDoS) and beast force web assaults. The sheer volume and variety of assault examples make it an optimal possibility for far reaching examination and assessment of detection systems [12].

C. CIDDS-001

The Coburg Intrusion Detection Data Sets (CIDDS-001), stand apart as a noticeable dataset for network-based intrusion detection, flaunting roughly 32 million records with 14 credits. What sets this dataset separated is its broad inclusion of assault types, incorporating a stunning 92 particular classifications going from Savage Power to Ping Outputs. The wealth and granularity of this dataset make it an important asset for scientists looking to investigate the full range of organization intrusion situations [13].

D. KDD99

The KDD Cup 99 dataset, beginning from 1999 under the support of the Guard Progressed Exploration Ventures Organization (DARPA), addresses a primary asset in the field of intrusion detection. In spite of its age, this dataset remains profoundly significant, containing around five million records with 41 features. Its attention on essential assault types, for example, DoS, test, Client to Root (U2R), and Remote to Nearby (R2L) gives important bits of knowledge into the early scene of digital dangers and the viability of detection procedures. [14].

E. UNSW-NB15

Delivered in 2015 by the Digital Reach Lab, the UNSW-NB15 dataset offers a cutting edge viewpoint on intrusion detection, highlighting 49 features and enveloping nine assault types. Its consideration of assorted assault classes, including Conventional, Exploits, and Observation, mirrors the developing idea of digital dangers in contemporary organizations. Additionally, its generally late delivery guarantees its importance in tending to ebb and flow difficulties in intrusion detection research [14].

F. UNSW-NB18

The UNSW-NB18 BoT-IoT dataset, an expansion of the UNSW-NB15 dataset, addresses a significant extension regarding information volume and assault groupings. With more than 72 million records and assault classes like Keylogging, operating system, and Information exfiltration, this dataset offers remarkable bits of knowledge into the complicated interaction between IoT gadgets and organization security. Its accessibility in different renditions, incorporating a consolidated variant with roughly three million records, gives adaptability for scientists fluctuating computational assets [15].

G. NSL-KDD

The NSL-KDD dataset fills in as an improvement to the KDD Cup 99 dataset, tending to weaknesses like information overt repetitiveness and copies. While its emphasis stays on essential assault classes steady with KDD Cup 99, its smoothed out construction and end of superfluous information make it a more productive and open asset for intrusion detection research [6].

H. UWF-ZeekData22

Arising in 2022, the UWF-ZeekData22 dataset addresses a spearheading exertion in network checking, utilizing imaginative information assortment procedures and examination strategies. With roughly 18 million records and 14 sorts of assaults, this dataset offers new bits of knowledge into arising dangers and weaknesses in present day organizations. Its joining with the open-source Zeek instrument further upgrades its utility for specialists and experts the same [16].

I. UGR'16

The UGR'16 dataset, custom-made for recognizing network security peculiarities, includes two unmistakable sets: Alignment and TEST. Laid out in 2016, this dataset catches a different exhibit of malware classes, including secure shell (SSH), spam, and port filtering. Its attention on abnormality detection highlights the developing significance of proactive safety efforts in alleviating arising dangers [17]. Table I provides a summary of the characteristics of these datasets.

TABLE I. SUMMARIZES THE OVERALL CHARACTERISTICS OF ALL DATASETS

Dataset	Dataset Type	Records	Features	Number of attacks
CICIDS2017	Multi class	2830540	83	14
CIDDS-001	Multi class	31.959.175	14	92
CSE-CIC IDS2018	Multi class	16.232.943	80	6
KDD99	Binary class	4.898.430	41	4
NSL-KDD	Binary class	N/A	41	4
UGR'16	N/A	16.900.000	12	7
UNSW-NB15	Multi class	2.540.044	49	9
UNSW-NB18	Multi class	3.668.522	42	6

In spite of the lavishness and variety of these datasets, a common worry across each of the nine is information lopsidedness. The lopsided conveyance of assault occasion classes and the striking inconsistency between ordinary traffic cases and those addressing different assault classifications present huge difficulties for intrusion detection research. Tending to these irregular characteristics requires cautious thought of examining procedures, highlight determination, and algorithmic ways to deal with guarantee vigorous and dependable detection capacities.

IV. COMMON STRATEGIES FOR ADDRESSING IMBALANCED DATA

Dealing with imbalanced data has emerged as one of the most formidable challenges in the field of machine learning. Studies have proposed various approaches to mitigate this issue, encompassing data sampling, cost-sensitive analyses, ensemble learning, algorithmic methodologies, and more. These strategies can be categorized into three main types, as shown in Fig. 2.

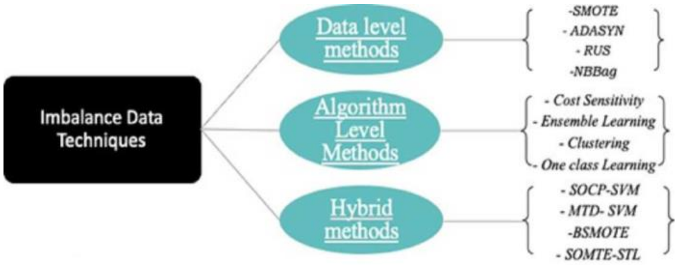

Fig. 2. Handling imbalanced data methods.

Extensive research has been undertaken to tackle the problem of data imbalance, particularly within network intrusion detection systems. This section provides an overview of select studies that examine these techniques. Table II presents a compilation of studies that have employed different approaches across the most widely used intrusion detection datasets to provide a comprehensive understanding of the diverse methodologies aimed at combating imbalanced data issues,

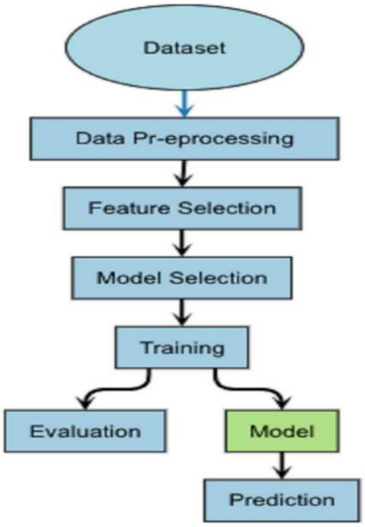

Fig. 3. Machine learning framework.

A. *Data-Level Techniques for Addressing Imbalanced Data*

- Data-level procedures include preprocessing steps pointed toward amending awkward nature inside datasets. These procedures, otherwise called outside strategies, try to accomplish information proportionality by either decreasing greater part class tests or increasing minority-class tests. Normal information level procedures include:

- SMOTE: SMOTE involves generating synthetic instances for the minority class by interpolating existing minority class instances [18]. A new specimen is created by selecting a random k-nearest neighbor (KNN) of an underrepresented instance and generating a value from a random combination of both interpolated instances. This method aids in spreading minority classes into the space occupied by majority classes, resulting in better defined decision boundaries.

- ADASYN: Sampling methods such as ADASYN enhance learning from data distributions by reducing the bias caused by class imbalances and reshaping classification boundaries toward challenging examples [31].

1) Used considerable amount of research has been conducted in the field of NIDS employing data-level techniques, as shown in Table II.

TABLE II. RECENT RESAMPLE TECHNICAL BASED NIDS STUDIES

Dataset	Technique	AI-based approaches		Year	Reference
		ML	DL		
NSL−KDD	SMOTE−ENN	No	Yes	2019	Zhang et al. [19]
CICIDS2017	Uniform Distribution Based Balancing (UDBB)	Yes	No	2019	Abdulhammed et al. [20]
CICIDS2017	SMOTE	Yes	No	2019	Yulianto et al. [21]
CSE−CIC−IDS2018	SMOTE	Yes	No	2020	Karatas et al. [22]
UGR’16	GAN	Yes	No	2020	Yilmaz et al. [23]
NSL−KDD UNSW−NB15	OSS and SMOTE	No	Yes	2020	Jiang et al. [24]
CIDDS-001 UNSW-NB15	SMOTE-STL	Yes	Yes	2021	Al and Dener [13]
NSL−KDD UNSW−NB15 CICIDS2017	ADASYN	Yes	No	2021	Liu et al. [25]
UNSW-NB15	SMOTE	Yes	No	2022	Ahmed et al. [26]
KDD99 NSL−KDD UNSW-NB15	SMOTE	No	Yes	2022	Meliboev et al. [27]
NSL-KDD	ADASYN	No	Yes	2022	Fu et al. [28]
UNSW-NB15	SMOTE	No	Yes	2023	Almarshdi et al. [29]
CICIDS2017 KDD99 UNSW-NB15	Ensemble method	Yes	No	2023	Thockchom et al. [30]
UWF-ZeekData22 UNSW-NB15	Random under sampling before splitting. Random under sampling after splitting. (B−SMOTE)	Yes	No	2023	Bagui et al. [16]

a) Ahmed et al. [26] proposed a NIDS framework using various machine learning schemes to detect network attack categories. The framework includes techniques such as data standardization, normalization, and SMOTE. This model achieved 95.1% accuracy on the UNSW-NB15 dataset.

b) Yulianto et al. [21] applied a similar technique to address data imbalance in their proposed IDS. They employed principal component analysis (PCA), ensemble feature selection (EFS), and SMOTE to enhance AdaBoost-based IDS performance on the CICIDS2017 dataset, achieving accuracy, precision, recall, and an F1 score of 81.83%, 81.83%, 100%, and 90.01%, respectively.

c) Karatas et al. [22] employed the CSE-CIC-IDS2018 dataset to build an efficient IDS using the SMOTE technique, resulting in an average increase in accuracy of 4.01% to attain 30.59% accuracy across different machine learning models.

d) Meliboev et al. [27] applied machine learning and deep learning techniques to detect security attacks. They used SMOTE to enhance model performance on the UNSW-NB15, KDD99, and NSL-KDD datasets, achieving accuracy scores of 91.2%, 95.2%, and 82.6%, respectively.

e) Almarshdi et al. [29] developed a hybrid deep learning IDS using convolution neural network (CNN) and long short-term memory (LSTM) algorithms, combined with the SMOTE technique. This model achieved 92.10% accuracy on the UNSW-NB15 dataset compared to 89.90% for the basic CNN model.

f) Fu et al. [28] introduced the Deep Learning Network Intrusion Detection (DL-NID) model using bidirectional LSTM (Bi-LSTM) and attention mechanisms, incorporating the ADASYN technique. This model achieved an accuracy of 90.73% on the NSL-KDD dataset.

g) Liu et al. [25] also employed the ADASYN technique in their proposed IDS, achieving accuracy scores of 92.57%, 85.89%, and an impressive 99.91% on the NSL-KDD, UNSW-NB15, and CICIDS2017 datasets, respectively.

Table III illustrates the ratios of measures that were attained by researchers in each study before addressing the issue of data imbalance using data-level techniques. As can be seen, Liu et al. [25] attained the highest accuracy rate of 99.86% on the CICIDS2017 dataset. In contrast, the lowest accuracy score achieved was 55% in the study conducted by Meliboev et al. [27] on the UNSW-NB15 dataset.

Table IV illustrates the ratios of measures that were attained by researchers in each study after addressing the issue of data imbalance using data-level techniques. Liu et al. achieved the highest accuracy rate of 99.91% when applying the ADASYN technique in their study. Several NIDS models demonstrated improved accuracy after implementing various data-level techniques. For instance, Meliboev et al. conducted a study on the UNSW-NB15 dataset using the recurrent neural network (RNN) algorithm. Initially, they obtained an accuracy rate of 55%, but after applying the SMOTE technique, the accuracy increased significantly to 71.90%. These findings highlight the effect and importance of data-level techniques in enhancing NIDS performance.

TABLE III. RESULTS OF MODELS BEFORE HANDLING IMBALANCED DATA

Algorithm / framework	Dataset	Accuracy	F1-score	Recall	Precision	Reference
RF	UNSW-NB15	89.5%	73.7%	72.3%	77.3%	Ahmed et al. [26]
DT		88.5%	70.7%	72%	70.9%	
LR		82.2%	41.9%	42.3%	51.3%	
KNN		84%	53.3%	51.3%	57.8%	
ANN		85.2%	54.4%	54.6%	61.2%	
AdaBoost	CICIDS2017	-	-	-	-	Yulianto et al. [21]
KNN	CSE-CIC-IDS2018	98.52%	98.89%	98.52%	99.28%	Karatas et al. [22]
RF		99.21%	99.25%	99.2%	99.30%	
Gradient Boosting		99.11%	99.29%	99.11%	99.51%	
AdaBoost		99.69%	99.7%	99.69%	99.7%	
DT		99.66%	99.60%	99.66%	99.66%	
Linear Discriminant Analysis		90.80%	99%	99.11%	98.90%	
CNN	UNSW-NB15	85.8%	87.8%	99.4%	80.9%	Meliboev et al. [27]
LSTM		84.9%	87.7%	98.3%	79.2%	
GRU		57%	71.3%	97.3%	56.3%	
RNN		55%	71%	100%	55.1%	
CNN + LSTM		80.8%	85%	99.3%	74.4%	
CNN	KDD99	92.3%	95.2%	91%	99.8%	
LSTM		91.8%	94.7%	91.1%	98.6%	
GRU		90.7%	93.8%	88.70%	99.7%	
RNN		91.7%	94.6%	90.2%	99.4%	
CNN + LSTM		92.7%	95.2%	91%	99.8%	
CNN	NSL-KDD	78.8%	77.7%	65%	96.7%	
LSTM		76.2%	74.2%	60.2%	96.9%	
GRU		72.5%	68.5%	52.4%	98.7%	

RNN		63.2%	70.5%	56.2%	94.6%	
CNN + LSTM		85.5%	85.9%	77.1%	96.1%	
CNN + LSTM	UNSW-NB15	91.86%	91.7%	90.91%	91.8%	Almarshdi et al. [29]
Bi-LSTM+ attention mechanisms	NSL-KDD	-	-	-	-	Fu et al. [28]
LightGBM	NSL-KDD	89.79%	-	-	-	Liu et al. [25]
	UNSW-NB15	83.98%	-	-	-	
	CICIDS2017	99.86%	-	-	-	

TABLE IV. RESULTS AFTER HANDLING IMBALANCED DATA

Technique	Algorithm / framework	Dataset	Accuracy	F1-score	Recall	Precision	Ref.
SMOTE	RF	UNSW-NB15	95.1%	95.1%	95.7%	94.8%	Ahmed et al. [26]
	DT		94.7%	94.8%	95.4%	94.4%	
	LR		69.4%	56.2%	59.4%	61%	
	KNN		84.7%	83.1%	85.1%	82.2%	
	ANN		77.6%	71.5%	70.6%	76.2%	
SMOTE + EFS	AdaBoost	CICIDS2017	81.83%	90.01%	100%	81.83%	Yulianto et al. [21]
SMOTE	KNN	CSE-CIC-IDS2018	98.8%	98%	98.08%	97.92%	Karatas et al. [22]
	RF		99.35%	99.35%	99.34%	99.35%	
	Gradient Boosting		99.29%	99.3%	99.29%	99.3%	
	AdaBoost		99.6%	99.6%	99.61%	99.6%	
	DT		99.57%	99.56%	99.57%	99.56%	
	Linear Discriminant Analysis		91.18%	91.57%	91.18%	91.96%	
SMOTE	CNN	UNSW-NB15	91.2%	91.5%	96.1%	87.5%	Meliboev et al. [27]
	LSTM		88.9%	89.5%	94.8%	84.8%	
	GRU		77.9%	79%	83.2%	75.3%	
	RNN		71.9%	76.5%	91.3%	65.8%	
	CNN + LSTM		87.6%	88%	90.6%	85.5%	
	CNN	KDD99	95.2%	94.9%	90.7%	99.5%	
	LSTM		95.4%	95.1%	91.4%	99.4%	
	GRU		94.1%	93.8%	88.9%	99.1%	
	RNN		94.1%	93.6%	90%	98%	
	CNN + LSTM		95.2%	94.9%	90.8%	99.5%	
	CNN	NSL-KDD	79.3%	74.8%	61.4%	95.5%	
	LSTM		75.8%	69.2%	54.2%	95.4%	
	GRU		79.1%	74.5%	61.2%	95.4%	
	RNN		76.1%	71.7%	60.5%	88%	
	CNN + LSTM		82.6%	79.8%	68.9%	99.5%	
SMOTE	CNN + LSTM	UNSW-NB15	92.10%	90.11%	91.75%	92.85%	Almarshdi et al. [29]
ADASYN	Bi-LSTM+ attention mechanisms	NSL-KDD	90.73%	89.65%	93.17%	86.38%	Fu et al. [28]
ADASYN	LightGBM	NSL-KDD	92.57%	-	-	-	Liu et al. [25]
		UNSW-NB15	85.89%	-	-	-	
		CICIDS2017	99.91%	-	-	-	

B. Algorithm-Level Approaches

Algorithm-level approaches focus on enhancing the learning capacity of classifier algorithms with regard to minority classes. These methods are often referred to as internal approaches. Techniques such as adjusting the probability estimation or modifying class-specific costs can be employed to benefit minority classes [31].

1) Cost-Sensitive Learning: The cost-sensitive learning framework lies between internal and external approaches. This technique integrates both algorithmic and data-level modifications in a unified approach by altering the learning process and assigning costs to samples accordingly [13].

2) Ensemble Learning: Ensemble learning combines various methodologies to address imbalanced classes. Ensembles based on techniques such as bagging and boosting are commonly used to tackle class imbalance issues.

a) Thockchom et al. [30] employed ensemble methods, specifically the stacking ensemble technique, on the KDD99, CIC-IDS2017, and UNSW-NB15 datasets. The stacking ensemble combined Gaussian naïve Bayes (GNB), decision tree (DT), and logistic regression (LR) classifiers. The proposed model achieved high accuracy levels: 99.80% on CIC-IDS2017, 93.88% on UNSW-NB15, and 99.84% on KDD99.

b) Yilmaz et al. [23] proposed a model for intrusion detection using the UGR'16 dataset. They used generative adversarial networks (GANs) to address the issue of unbalanced data. The degree of balance in the training dataset was determined using multilayer perceptron.

c) Abdulhammed et al. [20] presented an anomaly-based IDS applied to the CICIDS2017 dataset. The imbalanced distribution in the dataset was handled using a uniform distribution-based balancing method. Performance metrics were calculated based on five classifiers: the random forest (RF) algorithm, a Bayesian network, linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA). The model achieved the highest accuracy of 98.80%.

C. Hybrid Approaches

Hybrid strategies amalgamate methods from both algorithmic and information levels in ideal extents. These methodologies consolidate the qualities of algorithmic and information level strategies while relieving their particular shortcomings, at last further developing order accuracy. Normal hybrid calculations include:

1) SOCP-SVM: Support Vector Machines with Second-Order Cone Programming.

2) MTD-SVM: Multi-Threshold Decision-Support Vector Machines.

3) B-SMOTE: Borderline SMOTE.

4) SOMTE-STL: Synthetic Minority Over-sampling Technique-SMOTE with Tomek Links.

Application of Hybrid Techniques for Handling Imbalanced Data

1) Jiang et al. [24] employed two methods to address data imbalance on the NSL-KDD and UNSW- NB15 datasets. They combined one-side selection (OSS) to reduce majority samples and SMOTE to increase minority sample sizes. A deep hierarchical network model integrating CNN with BiLSTM achieved accuracy rates of 83.58% and 77.16%, respectively. Zhang et al. [19] also employed a hybrid sampling method combining SMOTE with edited nearest neighbors (SMOTE-ENN) to achieve an accuracy of 83.31% on the NSL-KDD dataset using CNN.

2) Al and Dener [13] utilized hybrid sampling with SMOTE and Tomek-Links Sampling (STL) to address imbalance in the CIDDS-001 and UNSW-NB15 datasets. Their Hybrid Deep Learning Approach combined CNN and LSTM algorithms, outperforming other deep learning and machine learning algorithms.

Trial review accentuate the power of information driven oversampling calculations in reinforcing base classifier execution, really tending to irregularity issues across different models, including AI and profound learning. The SMOTE has demonstrated success in diverse domains by creating new minority instances, circumventing overfitting and promoting classifier generalization [32]. This approach effectively addresses imbalance issues across various models, including machine learning and deep learning.

V. Conclusions

All in all, this review has embraced an exhaustive examination of strategies for tending to class irregularity in interruption identification datasets, with an emphasis on the viability of different procedures. Through our examination, we have assessed the presentation of oversampling techniques, for example, Destroyed and ADASYN, revealing insight into their adequacy in moderating the difficulties presented by imbalanced information.

Our examination has added to the comprehension of how these strategies can be applied with regards to interruption location, giving bits of knowledge into their assets and impediments. We have emphasized ADASYN's notable effectiveness in rebalancing datasets and increasing classification accuracy in particular.

While our review takes care of many systems, it's fundamental to perceive the developing idea of interruption location research. While we zeroed in basically on oversampling procedures, there are different methodologies, for example, bunch based under-examining that warrant further investigation. This features the continuous quest for creative procedures to handle class unevenness in interruption location situations.

In synopsis, our review fills in as an important asset for scientists and professionals in the field, offering experiences into the present status of the workmanship and making ready for future progressions in tending to the difficulties of imbalanced information in network interruption location.

1) Statistical Analysis: To measure the exhibition of intrusion detection frameworks when applying SMOTE and

ADASYN oversampling methods, we look at the exactness, F1-score, review, and accuracy measurements straightforwardly as shown in Table V and Fig. 4:

TABLE V. AVERAGE TECHNIQUE LIST

Technique	Accuracy	F1-score	Recall	Precision
SMOTE	88.13%	86.96%	85.68%	90.68%
ADASYN	92.28%	89.65%	93.17%	86.38%

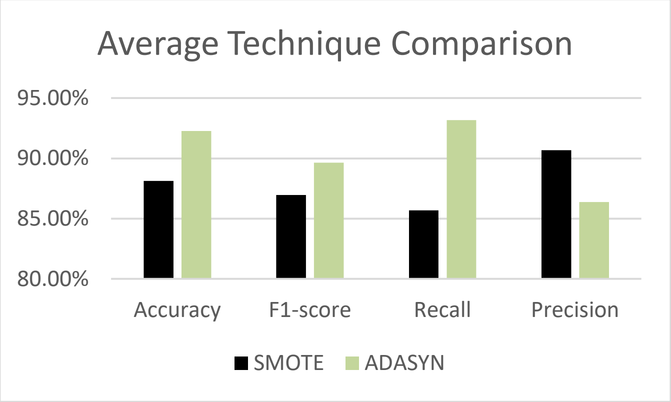

Fig. 4. Average technique comparison.

These discoveries exhibit that while the two strategies work on the general execution of intrusion detection frameworks, ADASYN gives better exactness, F1-score, and review, while SMOTE might be ideal for keeping up with higher accuracy.

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Roadmap for Generative Models Redefining Learning in Egyptian Higher Education

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***Abstract*—Artificial Intelligence (AI) Generative models have become powerful tools in all sciences, research, academia, and businesses. Egyptian Universities need to leverage those models while using them ethically and responsibly to survive in the current global market. This paper explains the evolution of those models, from basic natural language processing by IBM in 1954 to the current powerful revolutionary generative models. The paper presents research that helps us get desired outputs or behaviors from generative models through prompt engineering, chain of thought prompting and ReAct. The paper presents Egypt and Egyptian Universities readiness and steps taken to get advantage of the latest AI technologies. The paper examines the training of those models to identify their advantages and disadvantages for university members focusing on the Egyptian context. The roadmap for Egyptian Universities use of generative models consists of a SWOT analysis; an infographic of policies and guidelines with regard to faculty and students use of generative models at Egyptian Universities promoting academic integrity and innovation, while minimizing the risks associated with this technology; A table of types and severities of penalties for policy violations by students using generative models is specified and finally a framework for nontechnical users of generative models of reusable patterns to get the optimal desired output of the models is developed.**

Keywords—Artificial intelligence; generative models; prompt engineering; higher education; Egyptian universities

I. Introduction

This paper aims to provide a comprehensive framework for the use of generative models in Egyptian Universities. Generative Models are the current revolutionary artificial intelligence (AI) applications that act as our reliable, adjustable, and expert assistant in any research or learning process. Chatbots have automated and personalized services and processes across different industries. Generative models redefined our learning, instead of just using search engines like Google to access information now. We can use conversational engines like Google Bard or Microsoft Bing to not only get the list of sources but also get from it the relevant data presented and analyzed in the format we want. A review of universities adopting generative models and how those models evolved, highlighting their current rapid and revolutionary development is presented. Research on generative models' optimal use and Egypt readiness is examined to develop a roadmap for Egyptian Universities use of generative models.

II. Literature Review

A. *Universities Adopting Generative Models*

Egypt did not make generative models like ChatGPT officially accessible until November 2023 even though ChatGPT was officially introduced to the public in November 2022 [1]. As a result, Egyptian universities are lagging in the use of generative models. A recent study aiming at understanding how universities establish policies regarding the use of AI tools and exploring factors that influence their decisions analyzed top 500 universities according to the 2022 Quacquarelli Symonds (QS) World University Rankings. The study revealed that less than one-third of the universities had implemented ChatGPT policies. The use of generative models like ChatGPT in learning and teaching represented approximately 67.4% of universities, more than twice the number of universities that banned it. The study revealed that there are significant variations of university policies [2]. Generative AI is changing creative work as it can produce new content based on existing data, on creative work and workers. AI can augment human creativity, enhance productivity, and foster innovation through widely available online applications such as ChatGPT, Dall-E, and Midjourney. Today managers and leaders must leverage generative AI for their organizations and teams [3].

Harvard University, a leader and early adopter of generative AI explained, early in 2023 on its website, the concepts, and applications of generative AI and how it can create new content based on existing data. The web page provides guidelines for the responsible and ethical use of artificial intelligence at Harvard University. It covers topics such as data privacy, security, transparency, accountability, and fairness. It also provides examples of how AI can be used to advance research, education, and innovation at Harvard. The web page provides the vision and mission of the AI at Harvard program, which aims to foster collaboration and innovation in AI across the university. AI leaders and partners at Harvard can post their research on generative models. Through its website it showcases AI projects and research conducted by Harvard faculty and students, as well as AI tools and platforms available for the Harvard community. It provides resources and events related to AI education and innovation [4]. Generative models, despite their sophistication, have several limitations, GPT models still grapple with issues such as data biases leading to "hallucinations" or inaccurate outputs [5]. Birmingham University explained generative AI, how it can be used for teaching and learning, the benefits, and challenges of using it. It provided examples of generative AI tools and projects, as well as resources and guidance for educators and students [6]. Imperial College provided guidance for instructors and students on the use of generative AI tools, such as ChatGPT, for academic work. It explained the benefits and risks of using these tools, the ethical and academic implications, and the best practices for citation and acknowledgement [7].

B. *Generative Models Evolution*

Early developments that lead to current generative models started since 1954, with IBM and Georgetown University laying the background for natural language processing (NLP) through automating language translation [8]. In 1966 MIT researcher Joseph Weizenbaum created ELIZA, the chatbot that used pattern recognition and predefined rules to simulate human conversation, marking the beginning of NLP research [9]. In 1983, The Boltzmann machine modeled the probability of the entire network being in a certain state, where neurons influence each other bidirectionally and the strength of these connections is represented by weights, which are learned during training. The evolution of generative models from Boltzmann machines in 1983 to Transformers represent a series of breakthroughs in machine learning which include Deep Belief Networks (DBN) and Restricted Boltzmann machine (RBM) the neural network architectures used for feature learning, classification, and generative models [10].

In the 1990s, the advancements in machine learning took place as deep learning employed neural networks for data processing enabling the development of increasingly sophisticated language models. In 1997, Long Short-Term Memory (LSTM) networks enabled the development of deeper neural networks capable of handling larger datasets [11]. Since 2010 there was dramatic transformation of NLP, as in 2010 Stanford’s Core NLP suite provided algorithms for complex NLP tasks such as sentiment analysis and named entity recognition [12]. In 2011, Google Brain a deep learning artificial intelligence research team of Google AI, applied advanced resources and features like word embeddings allowing NLP systems to better understand the context of words [13].

In 2013, Diederik P. Kingma and Max Welling introduced the artificial neural network architecture Variational Autoencoders (VAE). VAE generates data by learning an approximation of the data's distribution, as the autoencoder has an encoder that maps input data to a lower-dimensional representation, and a decoder that reconstructs the original data from this representation [14]. Generative Adversarial Networks (GAN) developed by Ian Goodfellow and his colleagues in June 2014, enabled the creation of diverse and high-quality data samples that overcame initial training challenges and simplified the process of data representation and generation. GANs consist of two neural networks; the generator produces data samples from random noise, attempting to mimic the distribution of real data, while the discriminator tries to distinguish between real and generated data [15]. GANs enabled the creation of diverse and high-quality data samples. These early developments set the stage for the Transformer model, which has shown remarkable proficiency in tasks like text classification and sentiment analysis.

In 2015, Elon Musk and others endowed one billion dollars for the establishment of Open AI as a nonprofit organization to prepare against the unintended action of robotics and AI [16]. The aim was to have safe artificial general intelligence (AGI) as stated in Open AI mission: “Our mission is to ensure that artificial general intelligence—AI systems that are generally smarter than humans—benefits all of humanity” [17]. The introduction of Transformer models in 2017 revolutionized NLP. This architecture, trained on huge amounts of data, is a Large Language Models (LLM) that understands context and generates human-like text. The Generative Pre-Trained Transformer (GPT), GPT-1 introduced by Open AI in 2018, is a conversational LLM that has progressively increased in size and complexity. Elon Musk left Open AI board in 2018 and cut off funding as he criticized OpenAI’s partnership with Microsoft and was working on his own AI chatbot, TruthGPT. Microsoft invested $11 billion in OpenAI since 2019 and has exclusive access to its technology as it benefits from using OpenAI’s AI services in its products and platforms [18]. Since 2019, Microsoft’s cloud service Azure served as OpenAI’s exclusive provider of cloud computing services.

Generative AI has evolved rapidly since the release of ChatGPT in November 2022, research reveals that it could annually add to the global economy up to $4.4 trillion as it affects different industries, functions, and tasks, with marketing and sales, software development, and knowledge work.[19] In 2022, text-to-image models like Stable Diffusion, Midjourney and Dall-E generated images from textual descriptions. Dall-E uses Transformer architecture, the backbone of today’s NLP models, it is based on Contrastive Language–Image Pretraining (CLIP)'s ability to relate text to images, a neural network model developed by OpenAI, designed to understand, and link images with textual descriptions [20].

Open AI released ChatGPT to the public in November 2022, other companies released new iterations of generative AI on weekly basis. OpenAI’s ChatGPT, powered by GPT 3.5 an improved version of its 2020 GPT3 release, became the first widely used text-generating product, gaining a record one hundred million users in two months, making it the fastest-growing application at the time. As ChatGPT provided human-like conversations with users Microsoft integrated it with Bing search. During December LLM like Cohere supported more than one hundred languages, making it available on its enterprise AI platform and Google’s Med-PaLM trained for specific use cases and domains, such as clinical knowledge. During February Amazon’s Multimodal-CoT model incorporated chain-of thought (CoT) prompting, in which the model explains its reasoning, and outperforms GPT3.5 on several benchmarks; Meta’s LLaMA (Large Language Model Meta AI) became more efficient to use than some other models and Microsoft introduced Kosmos-1, a multimodal LLM that can respond to image and audio prompts in addition to natural language.

In March 2023 alone, there were six major steps forward, as Salesforce announced Einstein GPT, leveraging OpenAI's models, the first generative AI technology for customer relationship management; OpenAI released GPT4, which offers significant improvements in accuracy and hallucinations mitigation, claiming 40% improvement versus GPT3.5; Anthropic introduced Claude, an AI assistant trained using a method called constitutional AI, which aims to reduce the likelihood of harmful outputs; Microsoft announced the integration of GPT4 into its Office 365 suite, potentially enabling broad productivity increases; Google released Bard, an AI chatbot based on the Language Model for Dialogue Applications (LaMDA) family of LLMs; Bloomberg announced an LLM trained on financial data to support natural language tasks in the financial industry. While in April Amazon announced Bedrock, the first fully managed service that makes models available via API from multiple providers in addition to Amazon's own Titan LLM [21].

Chatbot AI the promising and disruptive technology automated and personalized various services and processes across different industries making major technology companies compete in the chatbot market, such as META, Anthropic, Deepmind, and Microsoft [22]. Currently Microsoft announced a new multiyear, multibillion-dollar investment with OpenAI, which is the third phase of partnership, following Microsoft's previous investments in 2019 and 2021, the renewed partnership is seen to accelerate breakthroughs in AI and help both companies engage in supercomputing at scale and commercialize advanced technologies in the future [23]. As of December 2023, ChatGPT has over 180 million users. Chat.openai.com website has around 1.7 billion visits per month [24]. OpenAI Chat GPT expects $200 million in revenues and $1 billion by 2024 [25].

C. Optimizing Generative Model Performance

Prompts are the way of communication with currently popular AI applications based on LLM's like ChatGPT. The quality of outputs from a conversational LLM is due to the quality of the prompts. Prompt patterns systematically guide LLMs enhancing interaction and task automation, providing a reusable solution framework to recurring problems. They provide a structured approach to customizing LLM output and interactions. Prompt Engineering is the art of crafting effective prompts to guide the responses of a machine learning model to achieve desired outputs or behaviors. Prompt engineering is a key strategy for enhancing the effectiveness and efficiency of generative models. Studies related to how best users of the models can craft their prompts classified prompt patterns into input semantics, output customization, error identification, prompt improvement, interaction, and context control [26].

Other research examining language models, including GPT-3 by OpenAI and LaMDA by Google, revealed that standard prompting is not always effective for reasoning tasks but Chain-of-thought prompting where generative models' users give an input, a series of reasoning steps, and an output, proved superior to standard prompting especially in arithmetic, commonsense, and symbolic reasoning. Users provide a step-by-step example of the way to solve a specific problem and the model follows the same sequence. This revealed the capabilities of generative models as it can learn from few natural language examples rather than relying solely on extensive training datasets. Chain-of-thought prompting enabled LLM's detail their reasoning before delivering an answer as users presented it with examples of such reasoning, making it generate its' own chains of thought. It got the model to break down multi-step problems, allowing for detailed reasoning, offering insight into the model's thinking, and facilitating debugging and understanding [27].

Other studies introduced ReAct methodology for the generative models to solve tasks by making language models both "think" (reason) and "do" (act). The models can interact with external information sources, like searching on the internet, and then adjust their reasoning based on what they find. As a generative model is capable of reasoning and acting, it does not just pull information; it thinks about what information to pull next, making its decision-making more dynamic. This method enabled the models to make plans, think of innovative ideas, and change their plans if something new comes up, it is like playing a game where it constantly must decide what to do next. ReAct Compared to other methods gave better results at answering questions, checking if facts are true navigating websites. When compared to other ways of teaching AIs, ReAct was better as the model learns with using few examples helping it make better decisions as it thinks through the problem [28].

D. Egypt's Preparedness for Generative Model Integration

Egypt readiness for generative models is clear in its national AI Strategy, which presents a comprehensive plan for integrating Artificial Intelligence (AI) into various sectors in Egypt, including education and university research. The strategy emphasizes the importance of building human capacity in AI, promoting AI research, and encouraging the integration of AI in university curricula and research projects. This is clear in its vision: "Exploit AI technologies to help achieve Egypt's development goals for the benefit of all Egyptians, and to promote Egypt's regional leading role to be an active global player in AI." Further to achieve its mission: "Create an AI Industry in Egypt, including the development of skills, technology, ecosystem, infrastructure and governance mechanisms to ensure its sustainability and competitiveness" [29]. It highlights the establishment of AI faculties in universities and the development of AI-related educational programs. A priority sector of Egypt AI strategy is Natural Language Processing (NLP) reflecting a strong commitment to integrating generative models and AI technologies in the educational sector. Egypt is producing the "Egyptian Charter on Responsible AI," which is based on the OECD AI Principles. This charter aims to include assessment guidelines, technical guidelines, and best practices for entities utilizing AI systems including universities [30].

Egypt developed various programs and collaboration among government agencies, private sector, and civil society to safeguard Egypt's ICT infrastructure and promote a secure digital environment [31]. Egypt Social Responsibility Strategy focuses on integrating technology in various social sectors including education [32]. Law No. 151 of the year 2020 provides a legal framework for the protection of personal data in Egypt as it establishes guidelines and regulations for electronic processing and control as well as penalties for violations of the law. [33] As the law outlines protection of personal data, and cross-border data transfer rules, it confirms with data subject rights regarding entering sensitive or confidential data into publicly available AI tools to protect privacy and conform to institutional information security policies. Egyptian Universities adhere to data privacy regulations and ensure the secure storage and handling of data this includes data used for training and deploying generative models.

Egypt has been a leader in educating its youth in the field of Artificial Intelligence as it established since 1996, the current Faculties of Computers and Artificial Intelligence to better reflect its educational mission and research focus. Those faculties support national educational objectives that include a strong emphasis on enhancing educational quality and integrating modern technology processes [34]. Egyptian Universities are working closely with government bodies and industry leaders to develop policies and guidelines for AI use in education and research. With regards to AI applications, Egyptian Universities established partnerships with tech companies specializing in AI and generative models to facilitate the exchange of knowledge and resources. One Example is Dell Technologies that has launched an initiative in collaboration with the Ministry of Communications and Information Technology (MCIT) to provide AI training in five Egyptian universities. This included workshops for university professors and students in AI and its applications, such as data science and big data engineering. Participating universities included Cairo University, Ain Shams University, the Arab Academy for Science and Technology, the American University in Cairo, and the German University in Cairo [35]. MCIT and The Egyptian Universities Network for Artificial Intelligence (EUNAI) a consortium of Egyptian universities work collaboratively on AI research and education offering resources and training programs related to generative models 36].

III. Pros and Cons of Generative Models in Egyptian Higher Education

In developing policies and guidelines for the use of generative models, Egyptian Universities should recognize that these engines are essential in teaching and research as they will change the way students learning and practice of humanities and Sciences, offering new products and services. Generative models redefined students learning process as they interact with the models to conduct conversational research to brainstorm summarize and analyze any topics of interest, they can understand new concepts by interactive simulations and games, and they can get advice on any issue [37]. Yet the model can create deepfakes, it may support events or hypothesis that are false and become convincing deceiving people. Students may copy the content in assignments without proper citation will result in the spread of cheating and plagiarism. Students should properly cite the use of AI tools using proper citation format adopted by most academic style guides [38], [39], [40]. Further studies have revealed that AI detection tools are still not reliable, several academic institutions do not recommend using the available automatic detection applications for academic integrity violations using generative AI, given their unreliability and inability to provide definitive evidence of violations [41]. OpenAI withdrew its detection software due to the software’s unreliability [42]. Criteria for approval to use generative models in assignments included academic justification, scope of use, source and type of generative model, data sensitivity and ethical implications, citation and transparency, review and approval process [43],[44],[45],[46]. Top universities presented types and severities of penalties for violations by students using generative models [47], [48].

There are disadvantages specific to Egypt and Egyptian Arabic speaking public universities context, as 59% of websites are in English and only 9% are in Arabic [49]. The results of an analysis of top ten million websites revealed that 60.4 % were in English and 1.1% was in Arabic. Yet from the years 2001 till 2011, the rate of online growth of the Arabic language use increased by 2,501% while it increased by 281% for English language [50]. Hyperscale data centers, which are ones with over 5,000 servers, are around six hundred in the world. Around 39% of them are in the US, while China, Japan, UK, Germany, and Australia account for about 30% of the total. This leaves the rest of the world 31% [51]. The share of internet users as a percentage of the population globally is 63%. In the developed world population, it is 90% while in the developing world it is 57% [52] [53]. Today’s popular generative large language models were trained on internet data these include AI applications developed by OpenAI the GPT-3,[54] DALL-E,[55][56] and Google BERT [57][58]. As Generative models were trained on internet data that is mostly in English presenting the English-speaking population, developed countries point of view. The model may generate content that does not confirm with the culture of the Arab world, it might produce biased information intentionally or unintentionally which may harm faculty members or students. The teaching in Egyptian public universities is in Arabic [59] with which the models may generate text but certainly it is not the language that it had much of its training in.

IV. Roadmap for Egyptian Universities use of Generative Models

The roadmap for Egyptian Universities use of generative models consists of a SWOT analysis; An infographic of policies and guidelines with regard to faculty and students use of generative models at Egyptian Universities promoting academic integrity and innovation, while minimizing the risks associated with this technology; a table of types and severities of penalties for policy violations by students using generative models is specified and finally a framework for nontechnical users of generative models of reusable patterns to get the optimal desired output of the models is developed.

A. *SWOT Analysis of Egyptian Universities*

The following is strengths, weaknesses, opportunities, and threats (SWOT) analysis on the use of Generative Models for Egyptian Universities that aides the development of a policy compatible with Egyptian laws, Artificial Intelligence strategy, cultural and social context. Table I is a SWOT analysis revealing the potential benefits of using generative models in education and research and the potential risks associated with the use of this technology, such as plagiarism and cheating.

TABLE I. SWOT ANALYSIS

Strengths	**Weaknesses**
-Conversational research, brainstorming, summarization, and analysis on any topic -Create interactive simulations and games that help learn and understand any concept -Provide consulting services	-Present biased content -Generate plagiarized content -Used in cheating -Create deepfakes that can be used to deceive people -Create harmful content
Opportunities	**Threats**
-Revolutionize the way Science and humanities taught and practiced. -Make better decisions in projects and research -Create products and services	-Generate reports against cultural and social context of Egyptians -AI detection applications may result in false negatives or positives -Spread of misinformation and harm of entities

B. *Policy Initiatives for Egyptian Universities*

The following is a suggested policy initiative to ensure that the use of generative models at Egyptian Universities is to promote academic integrity and innovation, while minimizing the risks associated with this technology. The National Council of Artificial Intelligence may collaborate with existing academic integrity committees in public universities and with faculty members to extend the responsibilities of the existing Academic Integrity Committee to review reports of academic misconduct involving generative models. The committee should be responsible for generative model risk assessment evaluating the ethical implications of their use in academic activities.

Based on Egypt AI strategy and aligned with the Universities Organization Law and its executive regulations Universities and Faculties should include the suggested policy statement: In accordance with Egypt AI strategy and The Universities Organization Law and its executive regulations, students must uphold academic integrity while also leveraging the potential of Artificial Intelligence (AI), including Generative Models, for academic endeavors. Use of AI is subject to faculty and instructors' approval. Acceptable uses of AI include idea brainstorming, initial draft creation, and language enhancement. The University prohibits the use of AI-generated content without proper citation or to complete assessments designed to evaluate individual skills. AI detection tools and human judgment may be employed to scrutinize submissions for AI-generated plagiarism. Faculty may require an oral examination to validate a student's understanding of any AI-assisted submissions.

1) Faculty guidelines: For University Faculty, Fig. 1 titled Faculty Guidelines for Integrating Generative Models into Coursework provides step-by-step guidelines. Changes in assignment design, submission protocols and grading rubric should take place to integrate the use of generative models. Faculty should review assessment methods to enable the development of AI resistant assignments and use oral examinations when possible. The Syllabus should include acceptable use that faculty will discuss in classes.

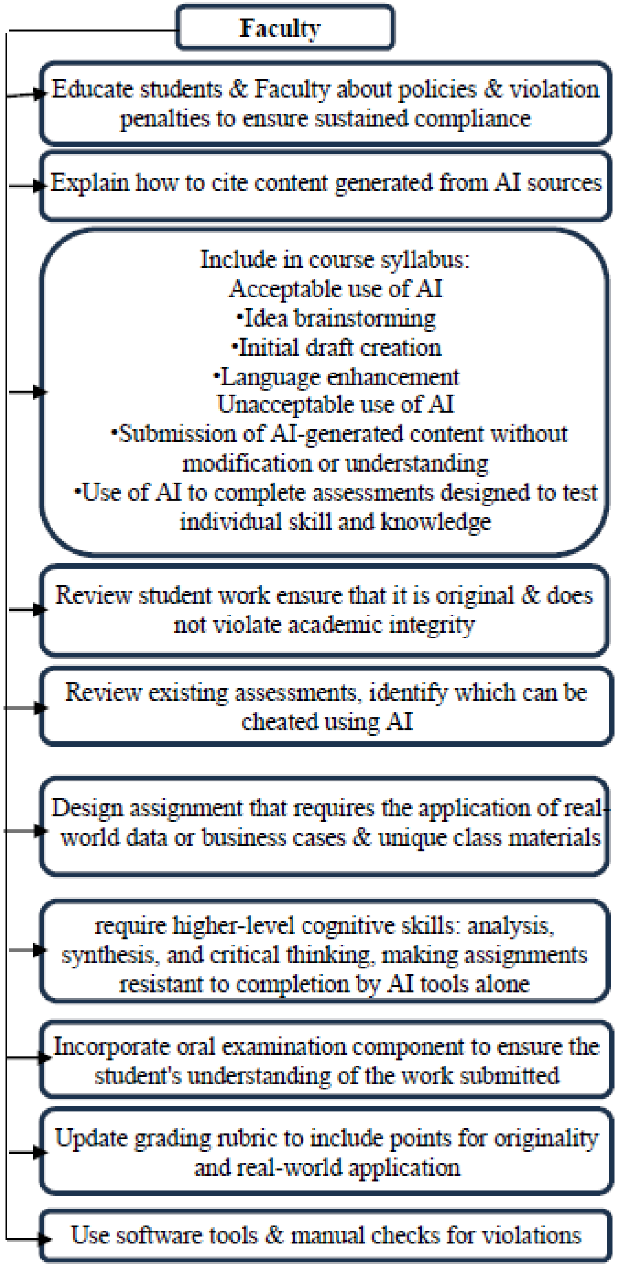
Faculty
Educate students & Faculty about policies & violation penalties to ensure sustained compliance
Explain how to cite content generated from AI sources
Include in course syllabus:
Acceptable use of AI
•Idea brainstorming
•Initial draft creation
•Language enhancement
Unacceptable use of AI
•Submission of AI-generated content without modification or understanding
•Use of AI to complete assessments designed to test individual skill and knowledge
Review student work ensure that it is original & does not violate academic integrity
Review existing assessments, identify which can be cheated using AI
Design assignment that requires the application of real-world data or business cases & unique class materials
require higher-level cognitive skills: analysis, synthesis, and critical thinking, making assignments resistant to completion by AI tools alone
Incorporate oral examination component to ensure the student's understanding of the work submitted
Update grading rubric to include points for originality and real-world application
Use software tools & manual checks for violations

Fig. 1. Faculty guidelines for integrating generative models into coursework.

2) Student guidelines: Student Guidelines for Effective Use of Generative Models in Courses. Fig. 2 include preliminary approval for the use of generative models, responsible use of AI and disclosure of their use. Students can use AI as a tool for data collection, brainstorming and Language enhancement enabling them to be creative and produce their own original work. Faculty should review the request based on these criteria and provide a decision within a reasonable period.

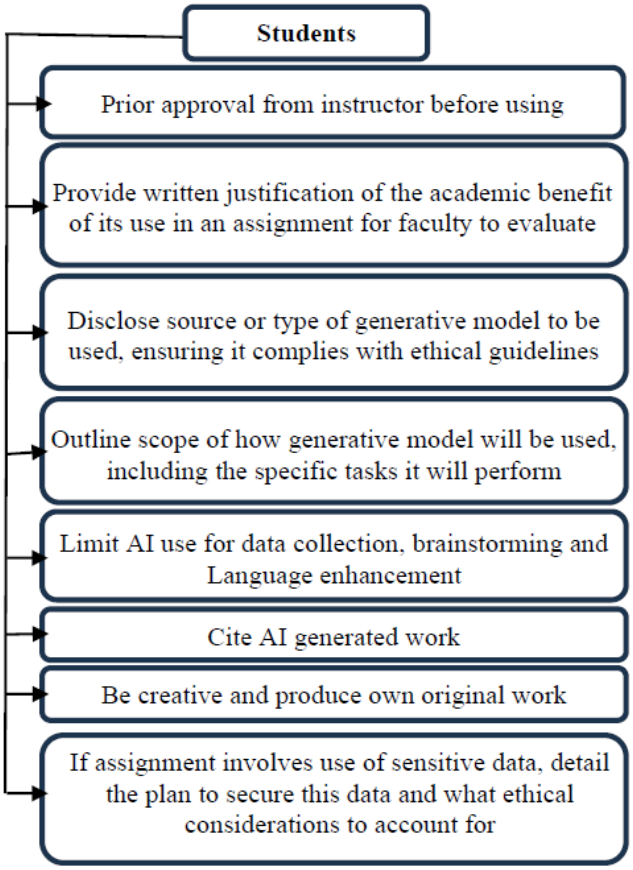
Students
Prior approval from instructor before using
Provide written justification of the academic benefit of its use in an assignment for faculty to evaluate
Disclose source or type of generative model to be used, ensuring it complies with ethical guidelines
Outline scope of how generative model will be used, including the specific tasks it will perform
Limit AI use for data collection, brainstorming and Language enhancement
Cite AI generated work
Be creative and produce own original work
If assignment involves use of sensitive data, detail the plan to secure this data and what ethical considerations to account for

Fig. 2. Student Guidelines for effective use of generative models in courses.

V. Penalties for Student Policy Violations

Penalties for misuse of generative models that fit the Egyptian Universities context include an academic integrity committee to investigate suspected AI-assisted cheating, apply penalties, and regularly review criteria for generative models use with the Egyptian national AI Committee. The academic integrity Committee should decide on the penalty depending on the infraction level ranging from minor, moderate, major to severe, and whether it is a first-time offense or more. Further students that feel that the review committee unfairly penalized them should file an appeal within fourteen days of the committee's decision. The following Table II provides examples of infraction severity and type of penalties applied depending on the number of times the students did the violation.

TABLE II. Penalties for Student Policy Violations

Severity / Type of Use	**Offense**		
	First	***Second***	***Third***
Minor: Unauthorized for non-graded class activities, not citing the use of a generative model in a homework assignment	Warning, requirement to attend integrity workshop	20% Deduction of assignment points	Failing grade for the assignment
Moderate: Unauthorized in graded homework assignments, group projects	50% Deduction of assignment points	Failing grade for assignment .	Failing the course
Major: To complete exams, final projects, or thesis work; instances of unauthorized use across several courses	Failing the course and academic probation	Mandatory integrity counseling	Expulsion from the university
Severe: To produce work that is published as original research without citation, plagiarizing on a scale that affects the university reputation	Possible legal action, expulsion from university	Students may file an appeal with the Academic Integrity Committee within 14 days of receiving penalty notice.	

VI. Framework for Optimal Generative Model Output

To get the best out of those models, Egyptian University members whether faculty, students, or administration should build their skills regarding prompt Engineering. Fig. 3 is an infographic for nontechnical users of generative models based on ChatGPT as it has the fastest growing number of users. In my proposed framework users should put in mind that it is useful to interpret the input, for example, when I entered in my prompt course syllabus, I identified that whenever I refer to "course code" it should refer to this course syllabus. It was further useful when identifying the use of common abbreviations instead of repeating the detail in each prompt of the conversation. Persona tailors the model response, for example respond as an information System professor, and further specify the audience as it differs in output sophistication for elementary school students or PhD Students in the field. Today's models can generate code to execute any instructions, create visualization images and graphs to whatever topics discussed through text to image instructions.

Generative models can, if given the steps show alternative results or asked for the steps of a certain result and use templates to generate output in specific structure. To avoid and check for errors the model can identify inaccuracies in its output and create a list of facts that need validation. If it refuses to answer a question the question can be sub divided or rephrased. Further the model can switch roles with the user as it gathers through questions all the data from the user necessary for it to generate the output. The User may present any rules and the model can participate in any game presenting simulations and automating its output. Once the user refers to key aspects in a conversation the model can maintain context, it can provide step by step explanations given a certain input and output showing how to arrive at the desired result using users' resources. The model can reason as it accesses external information whether available over the internet or given to it by the user as attachments and based on this information it will adjust its output. Once you provide an example of how a process should be, it will follow the same process on different data.

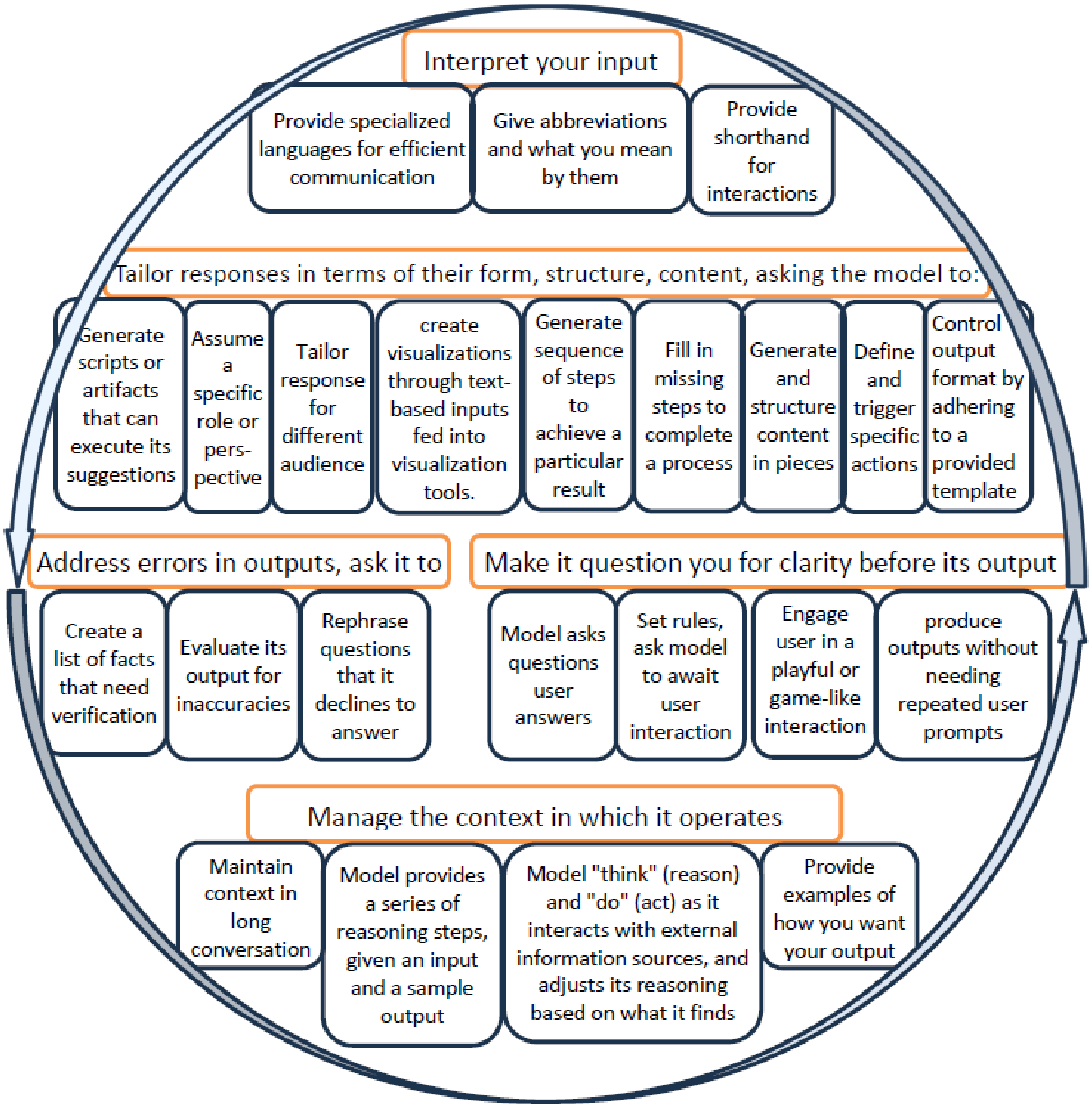
Interpret your input
Provide specialized languages for efficient communication
Give abbreviations and what you mean by them
Provide shorthand for interactions
Tailor responses in terms of their form, structure, content, asking the model to:
Generate scripts or artifacts that can execute its suggestions
Assume a specific role or pers-pective
Tailor response for different audience
create visualizations through text-based inputs fed into visualization tools.
Generate sequence of steps to achieve a particular result
Fill in missing steps to complete a process
Generate and structure content in pieces
Define and trigger specific actions
Control output format by adhering to a provided template
Address errors in outputs, ask it to
Create a list of facts that need verification
Evaluate its output for inaccuracies
Rephrase questions that it declines to answer
Make it question you for clarity before its output
Model asks questions user answers
Set rules, ask model to await user interaction
Engage user in a playful or game-like interaction
produce outputs without needing repeated user prompts
Manage the context in which it operates
Maintain context in long conversation
Model provides a series of reasoning steps, given an input and a sample output
Model "think" (reason) and "do" (act) as it interacts with external information sources, and adjusts its reasoning based on what it finds
Provide examples of how you want your output

Fig. 3. Generative model communication framework.

VII. Conclusion

In conclusion, this paper provides a comprehensive framework for the use of generative models for Arabic speaking, developing countries focusing on Egyptian Universities. A roadmap for the use of generative models in redefining the learning is developed. The research presented SWOT analysis on the use of Generative Models for Egyptian Universities where general factors applicable to all academia worldwide and other factors specific to Egypt were analyzed. Further, a policy that is compatible with Egypt laws, initiative, and cultural and social context was developed. This included key aspects of step-by-step guide for faculty inclusion of generative models in curriculum and students use of the models, in addition to a matrix of types and severities of penalties for policy violations by students using the models. This paper proposed an infographic of patterns that work for non-specialized students to get the best out of the generative models' capabilities. The framework is a reference for current generative models' capabilities in communicating with users. Finally, Universities should adjust their policies based on an ongoing monitoring of the actual use of generative models.

VIII. Future Work

Potential directions for further research could include cross-cultural comparative studies as Egyptian universities and universities from different regions with diverse cultural and legal frameworks could be compared to provide insights into how generative models are adapted globally. To fine-tune policies and educational strategies over time, longitudinal studies may be conducted to assess the impact of implementing generative models in the curriculum on students' learning outcomes, faculty teaching methods, and overall academic integrity. Universities should increase adoption and effective use of AI through working on technology acceptance modeling to understand faculty and students' attitudes towards generative models and factors influencing acceptance and resistance of generative models.

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A Smart Framework for Enhancing Automated Teller Machines (ATMs) Fraud Prevention

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***Abstract*—Over the past years, clients have largely depended on and trusted Automated Teller Machines (ATMs) to fulfill their banking needs and control their accounts easily and quickly. Despite the significant advantages of ATMs, fraud has become a very high risk and danger. As it leads to controlling all clients' accounts. In this paper, the proposed framework is using the iris recognition technology combined with the one-time password (OTP) to detect and prevent the known as well as the unknown attacks on ATMs and provide a table of the attackers and the suspected attackers with a counter to take a preventive action with them. Our proposed preventive actions are: card withdrawal, flagging the identified iris as an attacker in the database, notifying the card owner with this suspicious behavior, reporting to the Central Bank of Egypt (CBE), and calling the police when an attacker's iris counts three capturing times, even if for a different card. Two case studies were attempted to achieve the highest accuracy, the first case was using the Chinese Academy of Sciences' Institute of Automation V1.0 (CASIA-IrisV1) dataset using the Cosine Distance. The second one was using the Indian Institute of Technology Delhi (IITD) dataset using k-Nearest Neighbors (KNN) and Histogram of Oriented Gradient (HOG) techniques together reaching 100% accuracy.**

Keywords—Automated Teller Machines (ATMs); digital banking; image processing; iris recognition; One Time Password (OTP); machine learning; fraud detection; fraud prevention; biometrics; security; banking

I. Introduction

Automatic Teller Machines (ATMs) provide a non-stopping banking services without any time or place limitations [1, 2], which gives it this huge importance worldwide. It allows cash withdrawal, cash deposits, checking the account balance, paying bills and many other banking services over 24 hours / 7 days.

Despite all these advantages, ATMs are a very risky banking channels if they are not provided with the right security methods [3]. The current ATM framework was designed to avoid this risk, the current framework is that ATMs are designed with the Personal Identification Number (PIN) as the main authentication factor and some monitoring cameras to record all the daily interactions.

However, this design does not provide the required protection as the PIN has not become a very safe authentication technique [4], as when ATM cards are lost or stolen, an unauthorized user can get and enter the correct PIN and access all the clients' accounts and money [5]. In addition, this monitoring tool is insufficient because of the lack of security guards and because the human factor is the only monitoring factor, this security design is not helpful for detecting or preventing ATM fraud. This can be helpful after a fraud occurs.

The current – after fraud - scenario is that the client receives an SMS from the bank saying that he made a withdrawal with a specific amount, then the client begins to realize that he is a fraud victim and starts to report this fraud and asks for this video to check who is the criminal. In most of these cases, clients cannot get their money back or find the criminal. As the number of ATM users is growing daily because of the digital transformation awareness and the high increase in the number of deployments of new ATMs in addition to the increasing economic impact of the banking services [6]. So, detecting the fraud or the criminal is not enough as a preventive action all the time. As the same criminal can do this fraud in many other places with many different clients easily without detecting that he is a recorded criminal.

In this paper, a framework is proposed by using the iris recognition for the authentication of ATMs which can automatically detect and prevent the known as well as the unknown attacks on ATMs. Iris recognition is an advanced biometric technology that is used for detecting and identifying human iris from an image or video. It has many benefits that make it a perfect solution for the ATMs authentication. One of these benefits is that they are stable and unique over the whole life.

The biometric authentication became an important concern for many researchers because of the huge continuous wave of ATMs attacks worldwide. It is the process of identifying whether a specific person is the authorized person or not using a unique biological characteristic such as the fingerprint, face recognition, Iris recognition, voice recognition, behavior authentication and many other types [7, 8]. It works by comparing the enrolled biometric in the database with the person's captured biometric to authenticate. That is what makes it very helpful in the fast transactions-based authentications, as it is fast, accurate and not forgettable.

Iris recognition is an advanced biometric technology that is used for detecting and identifying human iris from an image or video. It has many benefits that make it a perfect solution for the ATMs authentication. One of these benefits is that it is stable and unique over the whole life [9]. The biometric authentication has been a very important concern for many researchers due to the huge continuous wave of attacks all over the world [10]. Biometric authentication is the process of identifying whether a specific person is the authorized person or not using a unique biological characteristic such as the fingerprint, face recognition, Iris recognition, voice recognition, behavior authentication and many other types [11]. It works by comparing the enrolled biometric in the database with the person's captured biometric to authenticate. That is what makes it very helpful in the fast transactions-based authentications, as it is fast, accurate and not forgettable [12].

Our paper is organized as the following: Section I which is an introduction of our paper including all the related topics of our framework. Followed by Section II, which gives a background about fraud and some biometric technologies with a comparison of how much they are effectively works to prevent any fraud. Then Section III, which includes a sample of other similar researches that were taken as a reference while our study. Then Section IV, which proposes our framework with two case studies to achieve the highest accuracy, followed by Section V which presents the structure of the database of our proposed framework. Then Section VI provides our experimental setup showing how our framework was implemented to get the case studies' results. Then Section VII, which presents the research contribution showing how our workflow overcomes the limitations of the other proposed solutions. Then in Section VIII we will present our results. And finally, Section IX concludes the paper.

II. Background

Fraud has many increasing techniques when it is related to the banking sector. It may be direct to the banking channels by stealing the card itself, the client's credentials, and many other direct ways. Or through any other way like the social media for example, which has been increasing and by sequence affects the banking sector which makes it a must to consider the information credibility as a very high concern to be considered at any fraud detection and prevention solution including all its perspectives [13]. It had been noticed also that the gap that allows the fraud to increase is the spread of using the technology by all its applicable tools without giving an attention to the relation between the more advanced the current technologies are and the greater the risk of the leakage of our data security and privacy [14].

For the example of social media, we are currently facing a very increasing phenomenon of customizing fraud campaigns over the social media and SMSs using some fake information and news to be able to steal the clients' banking data, which leads to being able to attack their banking channels and take their money [15, 16].

Noting that the fraud process is not necessary to start from the attacker's side, as sometimes the user is the initiator of this fraud, by listening to the spreading social media fake news (specially the Facebook as it is the most influencing social media application) and aim to gain more money and benefits then enters his banking or financial data to an untrusted source [17, 18].

There are various techniques that can be used to authenticate using biometrics. Below is a comparison in Table I:

TABLE I. COMPARISON OF THE BIOMETRIC TECHNOLOGIES

Biometrics	Cost	Accuracy	Performance	Flaws	Stability
Iris	High	High	High	Lighting	High
Retina	High	High	High	Glasses	High
Face	Medium	Medium	Medium	Beard, Glasses, Age	Medium
Fingerprint	Low	Medium	Medium	Dirt, Dryness	High

III. Literature Review

In this section we will provide a view of the historical researches about the iris authentication and how researchers used it to detect the ATM fraud actions and enhance the ATM security.

After reviewing several studies, we found that some researchers used only the iris recognition as a single authentication technique, while some of them used it in cooperation with other techniques also.

Some researchers used the multi-factor authentication approach, Akinola Kayode E. and his colleagues, (2019) proposed in their paper they used the iris recognition with the PIN to obtain the benefit of both the accuracy, the low cost (compared to the other approaches), the small size of its tool, the easiness of its programming language, and to avoid the risk of using only the PIN. The results of their paper were that the Fake Acceptance Rate (FAR) was 0% while Fake Rejection Rate (FRR) was found to be 99.94% which means that it was not possible for any fraudster to match the identity of another user in the database. There was 1.6% of the authentic users got denied access, which is small amount. ATM users should be security focusing while withdrawing money to prevent forced withdrawals. However, using the PIN with the iris is useless as a security with, it is just making the ATM journey timing longer which is against the purpose of the ATMs [19].

Other research such as Joyce Soares and A.N.Gaikwad, (2016) didn't only decide to replace the current ATM system with another biometric system using the iris recognition and the fingerprint to authenticate. But also protected the ATMs terminals from the thieving attacks and from the fire danger by making provisions of the pump motor and a direct current (DC) motor for rolling the shutter. Their system uses two techniques each for each recognition type. The Circular Hough Transform for iris recognition and the minutiae matching algorithm for fingerprint recognition. From the technical perspective, they used the ARM7 (a processor) based LPC2148 (a microcontroller) controlling to make the accessing process easy and smart. Their system's results provide the average accuracy of the overall system is 91.6% and the of these biometric technologies: average equal error rate is 0.076 in addition to securing from the fire and thief attacks. It also shows that the taken time for whole the ATM transaction is less than 10 seconds per user. After analysis, they mentioned that the accuracy and the security of this system is maximum and reaches up to 95%. However, they lost the main purpose of the

ATMs, which is the fast timing of making financial banking interactions. Also, if the user used the choice of the fingerprint, he/she will face a hygienic risk [20, 21].

Mohamed A. Kassem and his colleagues, (2014) noticed the high risk of attacks on the ATMs. So, they decided to make a framework that is secured an also fast using the multimodal biometrics. But to choose the right biometrics to be used they followed some criteria like the universality, uniqueness, permanence, measurability, performance, acceptability, and the circumvention. The main purpose of this proposed system is to reach a higher performance than using only a single biometric system. After passing the above-mentioned criteria to choose the right biometrics, they decided to use the fingerprint and the iris together as they are having the most acceptance of people than face recognition for example and based on the availability of their integration devices. However, they lost the main purpose of the ATMs, which is the fast timing of making financial banking interactions. In addition, if the user used the choice of the fingerprint, he/she will face a hygienic risk [22].

N.Geethanjali and K.Thamaraiselvi, (2013) proposed a system that is not only based on the multimodal biometrics, but also on the two levels of authentication in the ATMs. The system provides three choices of the multimodal biometrics during the authentication: Fingerprint and Iris, Iris and Face, Face and Fingerprint. The user can choose any system of them based on the biometrics that he wants to enroll for the verification to be authenticated. If the user failed to authenticate because of any reason, the user will be directed to a second choice of verification using another two biometrics. This will make the false acceptance rate (FAR) and the false reject rate (FRR) decrease and ensure a high level of security. However, they lost the main purpose of the ATMs, which is the fast timing of making financial banking interactions. Also, if the user used the choice of the fingerprint, he/she will face a hygienic risk [23].

Other research used only the iris recognition technology, like Pratiksha, and her colleagues, (2020), they used the iris recognition as it offers a new solution for identifying, authenticating and securing the user by analyzing the random pattern of the iris. Their iris system works by recognizing the person from an eye image and comparing it to the human iris pattern that is already stored at the template database. They used CASIA database at their paper and applied their project using MATLAB. Their results after using 20 images for training, 10 images for testing to calculate some features such as the contrast, the energy and the homogeneity were that their proposed system ad recognition rate of 94.6 % using the probabilistic neural network (PNN) [9].

Abiodun Esther Omolara and his colleagues, (2019) proposed a system that solves the ATMs fraud problem using the FingerEye. Their proposed system passes with three phases. The FingerEye is a strong system that is integrated with the iris scanning authentication. They register the users' iris at the profile creation stage and analyze it then convert it into a binary code then store it at the bank database. Their target was not only to prevent the ATM fraud, but also to design a new solution that helps the clients with disabilities as the blind clients to use ATMs' services. The results were saying that the proposed solution has a competitive advantage than the other proposed solutions as it does not only mitigate the Shoulder-surfing attacks, but prevents all the possibilities of shoulder-surfing, eavesdropping, and man-in-the-middle attacks. They also found that they improved the efficiency of the system by making the average authentication time to be 1.4 seconds instead of the current timing which is 6.5 seconds (using the bin or the password). They were unable to test this solution on a blind client, but they concluded that the authentication will be also secured and faster. However, the proposed module is really a difficult & complicated workflow, as they are depending on many processes and tools to implement the framework. So, it loses the main purpose of the ATMs, which is the fast timing of making financial banking interactions [24].

Komal Marathe and Hemant Mande, (2019) decided to develop a system to protect the ATMs' consumers from any fraud. They proposed an application called "Face Recognition System" (FRS), which can identify the client from a captured digital image or even from a video. The normal technique of this system is to match the captures photo's facial features with the stored one at the database. But that is not everything, if they availed a strong lighting and learning, the future authentication trials and transactions will have a wide base with boarders to compare with in case of failing at the original account image comparing. In their system, when the face image gets captured, the face gets located, then the iris gets detected and scanned then compared with the captured image at the database. At the end, they found that using a 2D and 3D technology had protected the authentication security level of the ATM strongly [25].

S. Koteswari and his colleagues, (2012) applied the concept of visual cryptography (VC) in the iris recognition by implementing the cryptographic software using Matlab 7.9.A modified version which is a method of maintaining the security of the captured images. That happens by dividing the image into a random share with encrypting it using a key. And it will be decrypted also using the same key. Their proposed method focuses on protecting the iris templates that are saved at the database. They divided their proposal into two phases. The enrolment phase and the authentication phase. As a result of their proposed system, this identification system is quite simple requiring few components and is effective enough to be integrated within security systems that require an identity check. The errors that occurred can be easily overcome by the use of stable equipment. Judging by the clear distinctiveness of the iris patterns we can expect iris recognition systems to become the leading technology in identity verification in ATM banking [26].

IV. The Proposed Framework

After passing with all the previous papers, we can start with our proposed framework. In this paper we are proposing a multi-authentication framework that detects and prevents the fraud actions on the ATMs, that will be applied through using the iris recognition biometric technology at the authentication phase at the ATM with the One Time Password (OTP) as a second step authentication to allow the client to access his/her accounts. The following figure represents the proposed framework (see Fig. 1):

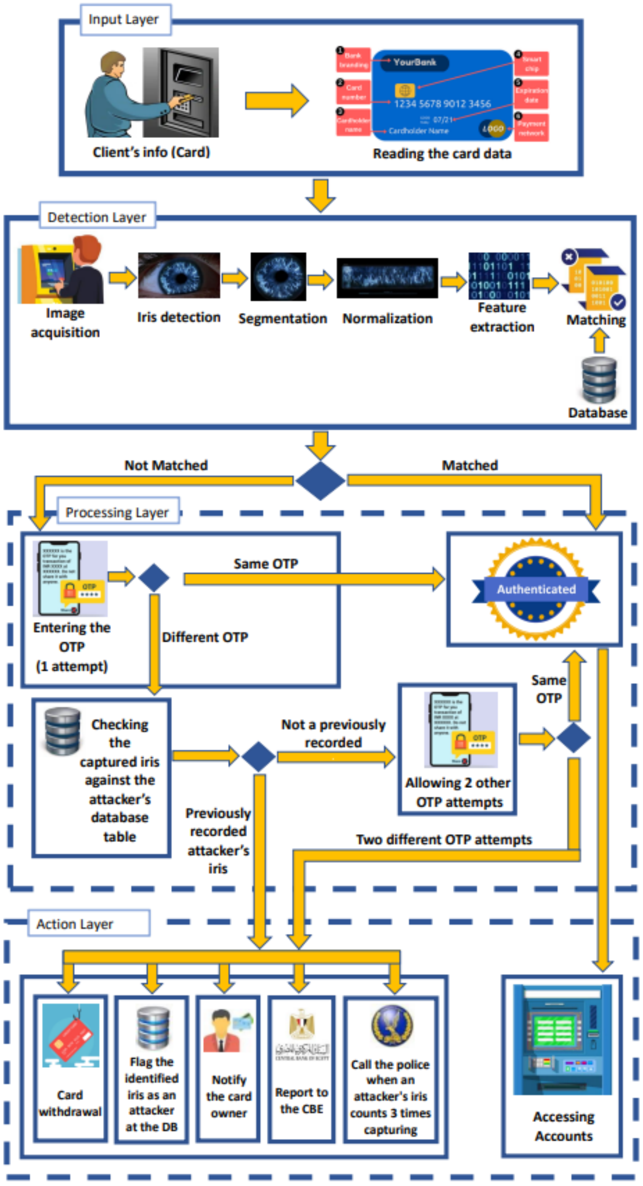


Fig. 1. The proposed framework.

In order to achieve the goal of our framework, we have gone through two case studies with two different techniques and datasets which gives us the ability to discover the most efficient and effective technique to achieve our main goal with this framework.

1) Case study (1): Our framework contains four layers (see Fig. 5), the input layer (see Fig. 2), the detection layer, the processing layer, and the action layer. It starts with the input layer, in which the client enters his card into the ATM, then the ATM starts reading the card data which includes the bank branding, the card number, the cardholder's name, a smart chip, an expiration date, and the payment network.

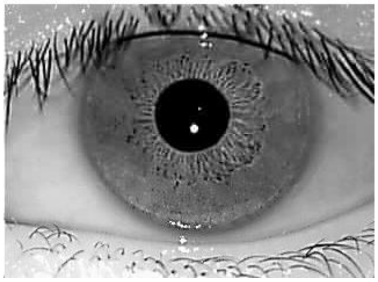


Fig. 2. The input layer.

Then it moves to the second layer, which is the detection layer, it includes the iris recognition cycle which starts with the user's image acquisition, and then it automatically detects the user's iris. After detecting the iris, this detected iris goes through another three steps before being matched with the database:

- Segmentation: In which the iris region gets isolated from the whole eye (see Fig. 3).

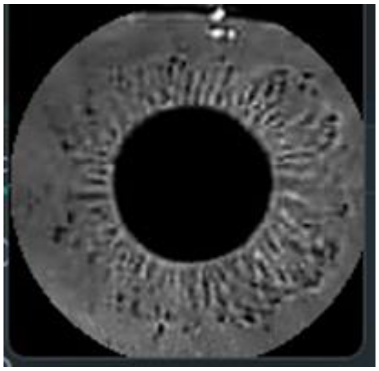


Fig. 3. The segmentation layer.

- Normalization: In which the segmented iris image gets transformed into a fixed size and dimensions to be ready for the next step (see Fig. 4) which is the feature extraction step. The below formula [27] is the normalization formula which was used at our framework:

$$\begin{gathered} I_n(X,Y) = I_o(x,y) \\ x = x_p(\theta) + \left(x_i(\theta) - x_p(\theta)\right)\frac{Y}{M} \\ y = y_p(\theta) + \left(y_i(\theta) - y_p(\theta)\right)\frac{Y}{M} \\ \theta = 2\pi X/N \end{gathered} \tag{1}$$

where, I_n is a $M \times\ N$ (64× 512 in our experiments) normalized image, $x_p(\theta)$, $y_p(\theta)$, and $\left(x_i(\theta) - y_p(\theta)\right)$ are the coordinates of the inner and outer boundary points in the direction θ in the original image I_0 [27].

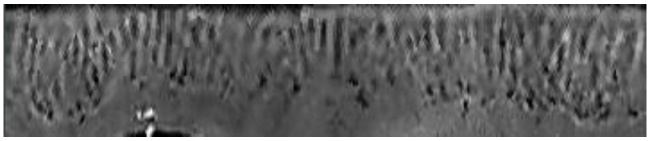


Fig. 4. The normalization layer.

- Feature Extraction: In this step, the normalized iris image gets converted to a set of parameters (mathematical parameters) to be ready to be easily matched with the database at the next step. The below formulas [27] are the feature extraction formulas which were used at our framework:

$$G(x,y,f)=\frac{1}{2\pi\delta_x\delta_y}exp\left[-\frac{1}{2}\left(\frac{x^2}{\delta_x^2}+\frac{y^2}{\delta_y^2}\right)\right]M_i(x,y,f),$$
$$i=1,2.$$
$$M_1(x,y,f)=\ cos\left[2\pi f\left(\sqrt{x^2+y^2}\right)\right] \qquad (2)$$
$$M_2(x,y,f)=\ cos[2\pi f(xcos\theta+ysin\theta)]$$

where, $M_1(x,y,f)$ denotes the modulating function, M_1 and in M_2 are the modulating function of the defined filter and Gabor filter, respectively, f is the frequency of the sinusoidal function, δ_x and δ_y are the y axis, respectively, the θ denotes the orientation of Gabor filter [27].

$$m=\tfrac{1}{n}\textstyle\sum_{\omega}|F_i(x,y)|\,,\quad \sigma=\tfrac{1}{n}\textstyle\sum_{\omega}\big||F_i(x,y)|-m\big| \qquad (3)$$

where, w is an 8 × 8 block in the filtered image, n is the number of pixels in the block w, and m is the mean of the block ω [27].

$$F_i(x,y)=\ \iint I(x_1,y_1)\,G_i(x-x_1,y-y_1\,)dx_1dy_1;$$
$$i=1,2 \qquad (4)$$

where, G_i is the ith channel of the spatial filters, $I(x,y)$ denotes the ROI, and $F_i(x,y)$ is the filtered image [27].

The last step at the iris recognition cycle and the detection layer is the matching step, in which the extracted feature gets compared to the stored one at the database during the enrolment phase to see if it is the cardholder or not. The following formula [27] is the matching formula which was used in our framework:

$$d_3(f,f_i)=1-\frac{f^T\quad f_i}{\|f\|\ \|f_i\|} \qquad (5)$$

where, f and f_i are the feature vector of an unknown sample and the i th class, $d_n(f,f_i)$ denotes the similarity measure, d_3 is the L1 distance measure, L2 distance measure (i.e., Euclidean distance) and cosine similarity measure, respectively. The feature vector f is classified into the mth class, which is the closest mean, using the similarity measure $d_n(f,f_i)$ [27].

It leads us to the next layer, which is the processing layer, in this layer; we will have two possible options: the first one is that the captured iris and the stored iris at the database are matched, and the second option is that they are not matched.

1) *If* matched, the user will authenticate normally and will be able to move to the action layer to access his/her accounts.

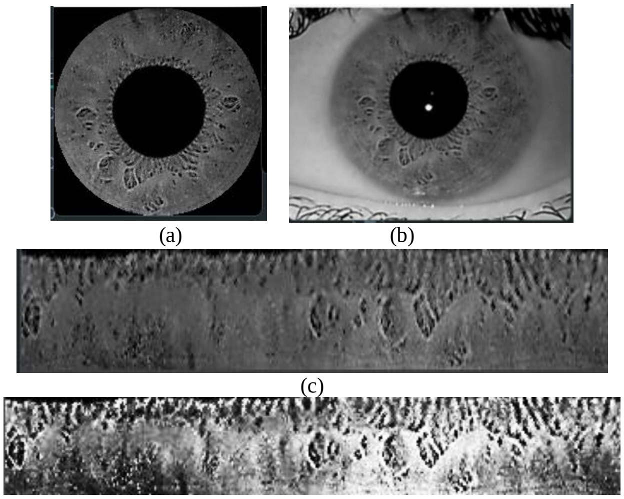
2) *If* not matched, the user will receive an SMS with an OTP on his/her mobile and will be asked to enter it into the ATM for a just one attempt. If it was the same OTP, then he/she will authenticate normally and will be able to move to the action layer to access his/her accounts. But if it is not the same OTP, then the system will start checking the captured iris against the attackers database table to check if it is a previously recorded attacker's iris or not.

If his/her iris got matched with any attacker's iris, then the system will move to the action- layer to take the below actions on the user as he/she will be detected as an attacker:

1) *Card* withdrawal.
2) *Flag* the identified iris as an attacker at the DB.
3) *Notify* the card owner.
4) *Report* to the CBE.
5) *Call* the police when an attacker's iris counts three times capturing, even if for a different card.

If not matched, then the user will receive another SMS with an OTP and will be asked to enter this OTP with only two attempts. If he/she entered the same OTP, then he/she will authenticate normally and will be able to move to the action layer to access his/her accounts. But if he/she entered a wrong OTP at the two attempts, then the system will move to the action layer to take the below actions on user as he/she will be detected as an attacker:

1) *Card* withdrawal.
2) *Flag* the identified iris as an attacker at the DB.
3) *Notify* the card owner.
4) *Report* to the CBE.
5) *Call* the police when an attacker's iris counts three times capturing, even if for a different card.



(a) (b)

(c)

(d)

Fig. 5. Image pre-processing (a) The original image (b) The segmented / localized image (c) The normalized image (d) The normalized image after enhancement.

2) *Case study (2):* Our framework at this case contains a pre-processing stage, which is the Image Pre-processing stage, as we are using here Indian Institute of Technology Delhi (IITD) dataset, which contains eyelashes and eyelids and are in many different sizes which affects the results efficiency. So, we will go through the Image Resizing to unify the iris images and make sure these are all with the same dimensions and suitable for the framework's best results by allowing it to get the same number of features from all the dataset's iris.

Considering also that there is a relation between decreasing the image’s size and the processing time [28] so, the images sizes became (200×200 pixels) after this stage.

The second stage is the Segmentation stage, at this stage the mission is to remove the non-useful surrounding regions of the iris by detecting the boundaries of both the iris and the pupil automatically which ease the feature extraction process of these images. As an output of this stage, we should have a ready image for the next stage which is the Feature Extraction stage. In this case study, we are using the Daugman‘s Integro-Differential operator technique for the iris segmentation which works by dividing the eye into two circles, the pupil and the iris, then detecting the center and radius of the pupil and the iris. The circle on the pupil explains the distance between the pupil and the iris then the circle on the iris shows the distance between the iris and the other parts of the eye. The third stage is the Feature Extraction, which is the most important stage and in which the needed and important features get extracted from the image and un-needed features are excluded. In our framework we will use Histogram of Oriented Gradients (HOG) for the feature extraction stage. In which the image gets divided into some cells, and each cell into some pixels. Now, we have arrived to the last stage at our framework which is the Classification stage, at this stage we have user K-Nearest Neighbor (k-NN) algorithm to be able to obtain the highest accuracy which works by finding the nearest neighbor object at the extracted feature space then gives an output that the entered iris belongs to which group of features.

V. Structure of Database

Fig. 6 shows the Entity Relation Diagram (ERD) that represents our proposed framework, it contains all the related parties of our framework and explains the relation between them. The “Attackers History” table includes all the history of any detected attacker, which has a many-to-one relation with the “Attackers” table, which counts the iris’s capturing time as an attacker. It also has all the required tables with all the data that helps at the fraud detection, prevention, reporting to the central bank of Egypt (CBE), and taking the right legal action.

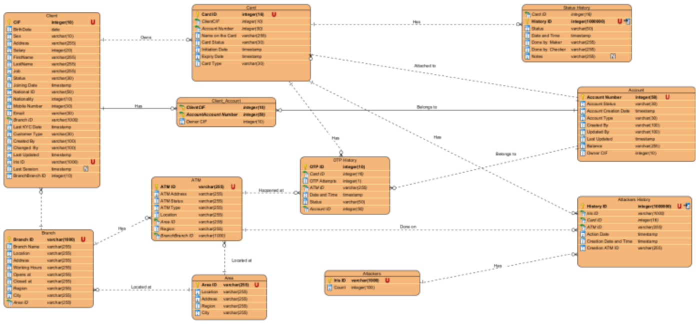


Fig. 6. Database Entity Relation Diagram (ERD).

VI. Experimental Setup

Due to the difficulty of implementing the proposed model at this stage in the real life because of its very high-cost hardware requirements, we decided to simulate the ATM device currently by a Graphical User Interface (GUI) that describes the customer interactions with the ATM into our framework. Below we will attach some highlights of our framework:

1) The main step that appears to the customer to enter his Card ID and the ID of the ATM he is acting with is a simulation to the physical card entering to the ATM and to upload his Iris as a simulation to the live scanning of his iris, then the client clicks on “Enter” (see Fig. 7):

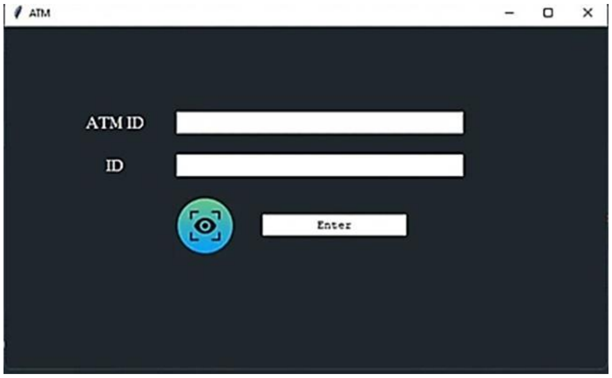


Fig. 7. The first step at our proposed system.

2) In case if the captured Iris was a wrong iris (not the iris of this card), then the client will be asked to enter the OTP the was sent to the mobile number of his card. So, the below screen simulates this step to allow the client to enter his OTP (see Fig. 8):

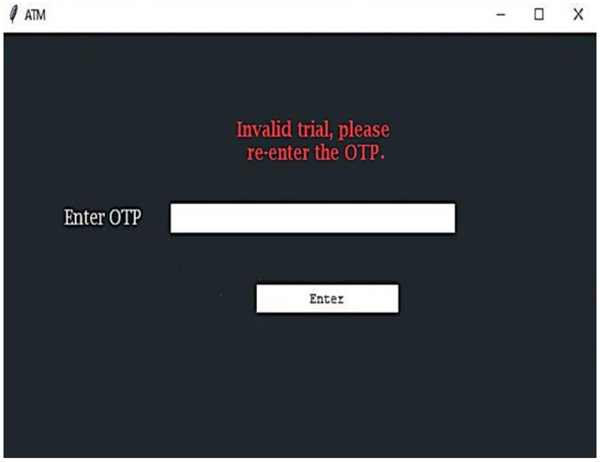
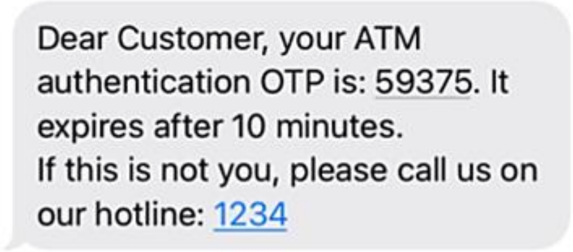

Invalid trial, please
re-enter the OTP.

Fig. 8. Case of capturing a wrong iris.

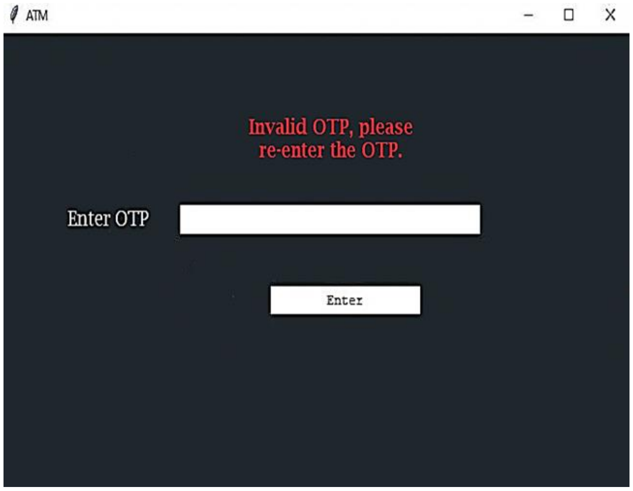
3) The OTP SMS that will be delivered to him from the SMS gateway with a random OTP (see Fig. 9):



Dear Customer, your ATM authentication OTP is: 59375. It expires after 10 minutes.
If this is not you, please call us on our hotline: 1234

Fig. 9. First OTP SMS

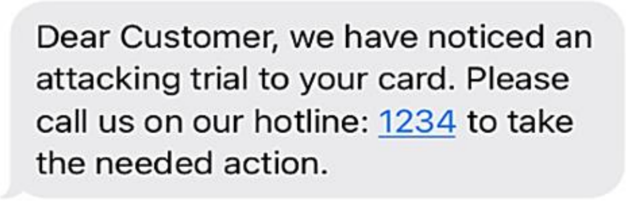
4) In case of entering a wrong OTP, the system will verify the captured iris against the attackers table first, then if it does not match with any attacker's iris, another OTP attempts will be allowed to him with two different SMSs (The third SMS will be sent to him only in case of entering a wrong OTP for the second time). The below screen shows the screen that asks the client to re-enter the OTP (see Fig. 10):



Invalid OTP, please
re-enter the OTP.

Fig. 10. Case of entering a wrong OTP.

5) *In* case of entering a wrong OTP for three times (even if in a different periods or ATMs), the card will be withdrawn, and the customer will receive the below SMS at the mobile number of his card (see Fig. 11):



Dear Customer, we have noticed an attacking trial to your card. Please call us on our hotline: 1234 to take the needed action.

Fig. 11. Case of entering a wrong OTP for three times.

VII. Research Contribution

Our workflow overcomes the limitations of the other proposed solutions as shown in the below Fig. 12, at this part we will explain all our contribution points in details:

1) Suitable to all cultures, as it does not need a specific level of knowledge, age, education or a specific culture to be used, it is just following the signs on the ground of the ATM to be able to allow the iris to be captured.

2) Achieves the main purpose of ATMs, which is making some banking transactions in a short time: as this framework balances between the high security and the effectiveness at the same time, as it is not complicated and does not take much time to authenticate with.

3) Prevents ATMs fraud, not just detects it: as the main idea of our framework is to prevent the attacker from making any fraud on the card without limiting the client's needs from the service. So, in case of noticing any abnormal behavior, the card will be withdrawn, and a legal action will be taken with the attacker and his data.

4) Hygienic way to authenticate: as it is touchless, so, no way to transfer any virus or disease while authenticating.

5) Ensures a high level of security: as it uses the two factors authentication technique to make sure that if the iris recognition failed according to any surrounding reason, the OTP will pass.

6) In case of detecting a fraud action, the card will be withdrawn: to ensure the safety of clients' data and money, our framework will prevent the attacker from keeping the client's card with him, to avoid being used at any suspicious website that does not require an OTP.

7) Using the iris recognition to authenticate: as this technique is highly secured, unique, and can't be affected by age or illness. It avoids the weakness of the PIN and face recognition, avoids the complication of the other high-level biometric security techniques like the retina, and avoids the high hygienic risk of the fingerprint.

8) Uses the two factors authentication in case of failing at the iris recognition: this point achieves the required balance between making the business process runs smoothly and normally and ensuring a high level of security. As we always give the client another chance to validate that he is the card owner, not an attacker.

9) Reporting the attackers' details to the CBE: as this step ensures having a centralized database between all the banks and the governmental institutions with the attackers' data, which accelerates and facilitates avoiding any upcoming attacks and taking the right legal action in case of facing any attack.

10) Building a database table of the detected attackers with a counter: this step facilitates taking the right preventive action with the captured attackers and prevents the fraud from happening next time.

11) Calling the police when the attacker's iris counts three times capturing; this step will be an instant action to prevent the attacker if it was faster than the attackers' trials.

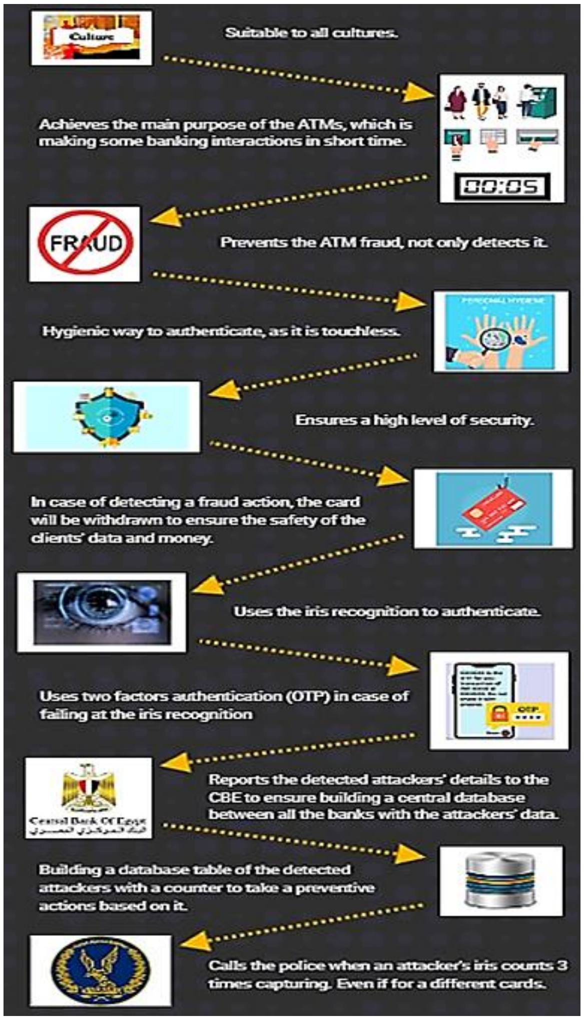

Culture
Suitable to all cultures.
Achieves the main purpose of the ATMs, which is making some banking interactions in short time.
00:05
FRAUD
Prevents the ATM fraud, not only detects it.
PERSONAL HYGIENE
Hygienic way to authenticate, as it is touchless.
Ensures a high level of security.
In case of detecting a fraud action, the card will be withdrawn to ensure the safety of the clients' data and money.
Uses the iris recognition to authenticate.
Uses two factors authentication (OTP) in case of failing at the iris recognition
OTP
Central Bank Of Egypt
البنك المركزي المصري
Reports the detected attackers' details to the CBE to ensure building a central database between all the banks with the attackers' data.
Building a database table of the detected attackers with a counter to take a preventive actions based on it.
Calls the police when an attacker's iris counts 3 times capturing. Even if for a different cards.

Fig. 12. Workflow overcomes the other solutions' limitations.

VIII. Results

For the case study (1), we selected to use the Chinese Academy of Sciences' Institute of Automation V1.0 (CASIA-IrisV1) [29] dataset currently at our module. It consists of 756 iris images from 108 eyes. For each eye, there are seven images captured in two sessions and stored in bitmap (BMP) format with a resolution of 320*280 pixels.

These 756 irises are specified as two main groups, the first group is for the iris that was captured at the first session, they are three images and used as a training dataset. While the second group is for the iris that was captured at the second session, they are 4 images and used for testing.

Using CASIA-IrisV1 dataset, we applied our framework on two different cases and ways.

1) The first one is using the original CASIA-IrisV1 dataset normally, where each folder contains the training and testing iris for the same person. In this case, the recognition results using Different Similarity Measures are as provided in Table II:

TABLE II. The Recognition Results Using the Original Dataset

Similarity Measures		Correct Recognition Rate (CRR) %	
		Original Feature Set	Reduced Feature Set (107)
1	**L1**	60.87963	66.203704
2	**L2**	54.398148	73.611111
3	**Cosine Distance**	54.398148	75.925926

We decided to work with the Cosine Distance as it provides the highest accuracy as shown above 75.925926%.

Which means that out of 107 irises, there are around 81 irises got matched successfully. However, there are 26 irises didn't get matched successfully due to many environmental factors.

Noting that reducing the feature set to "107" resulted into a higher accuracy and a lower computational power, as this reduction had reduced the confusion of comparing across many features.

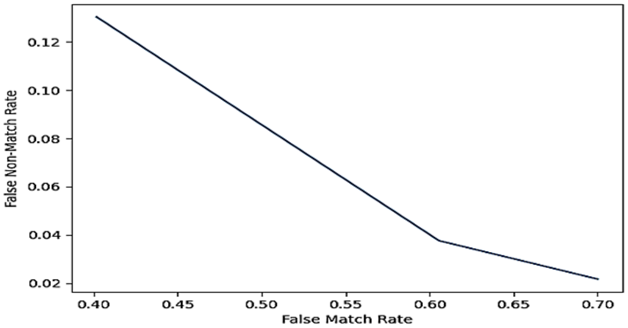


Fig. 13. Recognition results using cosine distance.

This graph in Fig. 13 describes the relation between the false non-match rate (FNMR) and the false match rate (FMR), the FNMR is when we compare the iris of someone to his other iris during the testing phase, and the results became another one's iris. So, it is a false non-match result. During the FMR is when we compare two different iris of two different people at the testing phase, and it results as the same iris. So, it is a false matching result. So, it is an inversely proportional relation between them as shown at the graph. The relation of coaptation (ROC) is calculated as: FMR/1-FNMR. At this case, the FMR and the FNMR are the percentage of the non-accurate results of the framework, this percentage of non-accuracy can be treated by the data augmentation. By increasing the training dataset, the module will be more trained and will have the ability to reach more accuracy and avoid any FMR or FNMR.

At each iris, we can extract many features to be used at detecting the iris owner, which takes a very high computational power. So, we reduced the taken features to be just 107 features. This graph in Fig. 14 shows that when we reacted 40 features extracted, we got the highest accuracy we need. So, at this point, we can close the program and get enough results. However, if we completed 107 features, we would reach highest accuracy that we can get using the extracted features, which is: 75.925926%.

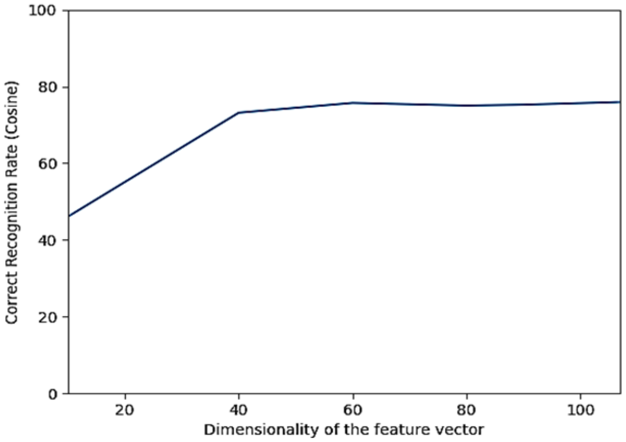


Fig. 14. Receiver Operating Characteristic Curve (ROC).

2) The second one is using CASIA-IrisV1 dataset but with applying some changes on it, by replacing the testing iris of each folder with another person's iris to check if it will be matched normally or not. In this case, the recognition results using Different Similarity Measures are as provided in Table III:

TABLE III. THE RECOGNITION RESULTS USING THE NEGATIVE DATASET

Similarity Measures		**Correct Recognition Rate (CRR) %**	
		Original Feature Set	**Reduced Feature Set (107)**
1	**L1**	1.388889	0.462963
2	**L2**	1.388889	0.462963
3	**Cosine Distance**	1.388889	0.462963

As shown at the above table, the resulted CRR is 0.46%, this very low accuracy rate is due to some human errors during capturing the iris dataset, which led to a FMR and FNMR by this percentage. So, we do recommend availing this framework at a very suitable environment by applying the ATMs shields as what is already happening at most of the banks, that will lead to getting the highest results and accuracy from the module.

For the case study (2), we have decided to use IITD (IIT Delhi [30] dataset using k-Nearest Neighbors (KNN) and Histogram of Oriented Gradient (HOG) techniques. We have selected to use the Indian Institute of Technology Delhi (IITD) database, this database is a bitmap format image database which was collected from the students and the staff of the Indian Institute of Technology Delhi (IITD) at July 2007 using JIRIS, JPC1000, and digital CMOS camera which consists of 2240 images from 224 different groups of users who are between 14-55 years (176 males and 48 females) 10 images gets registered for each user in an indoor environment. The resolution of each image is 320 x 240 pixels. The results of this combination were great! as it reached 100% accuracy with seven images for training and 3 images for testing as in Table IV:

TABLE IV. TESTING RESULTS OF USING (HOG) + (KNN)

Images Numbers Per Person	Training: 7 images Testing: 3 images	Training: 3 images Testing: 2 images	Training: 2 images Testing: 3 images	Training: 1 image Testing: 4 images
Accuracy %	100%	99.33%	98.21%	96.31%

IX. CONCLUSION

The technique of using the iris recognition combined with the OTP as a second step authentication is a reliable technique to secure the ATMs, as it provides a highly secured system with a fast timing to complete any financial transaction. In addition to our proposed model, which does not only succeed in achieving this security at a fast time, but also enhanced its prevention by providing a table of the attackers and the suspected attackers with a counter and a preventive action (notifying the user, notifying the bank, reporting to the CBE to centralize & share these data with the other banks, and reporting to the police). We also recommend by the end of our paper to use k-Nearest Neighbors (KNN) and Histogram of Oriented Gradient (HOG) techniques together to reach the highest accuracy (100%).

In the future, it is noted that the larger the dataset size we use, the better the accuracy we get. So, we are planning to use the other mentioned sources of data in our module to achieve the needed level of accuracy and to use the deep learning technology: Convolutional Neural Network (CNN). It is necessary to plan to enhance this model by cancelling the use of any cards to authenticate and by providing a suitable system for the users with disabilities to be able to do all their financial actions through the ATM normally.

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A Combined Ensemble Model (CEM) for a Liver Cancer Detection System

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***Abstract*—The liver is one of the most important organs in the human body. The liver's proper function is critical for overall health, and liver diseases or disorders can have serious consequences. Liver cancer is also known as hepatic cancer, which is divided into various types of cells that belong to the cancer. The most common type of liver cancer is hepatocellular carcinoma (HCC). HCC is one of the most common types of liver cancer that can affect up to 85% of people worldwide. Early detection of liver cancer is essential in healthcare because it increases the chances of successful treatment and patient outcomes. Many researchers have developed models that help detect and diagnose liver cancer. The first step in detecting liver cancer is identifying people at a higher risk. Chronic hepatitis B or C infection, cirrhosis, heavy alcohol use, obesity, and exposure to certain chemicals and toxins are all risk factors. This paper is mainly focused on detecting the cancer-affected regions that occur in the liver. In this paper, a combined ensemble model (CEM) for a liver cancer detection system is developed to find and detect liver cancer and liver disorders in their early stages. A pre-trained model, RESNET50 with transfer learning, is used to obtain the features from the pre-trained model—an advanced preprocessing technique involved in filtering the noise from input CT scan images. A hybrid feature extraction (HFE) technique also gets significant elements from the input CT scan images. Finally, the proposed CEM combines an Extreme Gradient Boosting (EGB) algorithm with a Recurrent Neural Network (RNN) that focuses on detecting the abnormal cancer cells present in input CT scan images. The performance of the CEM shows a high accuracy of 98.48% with a 10% high detection rate. Previously, it was 88.12%.**

Keywords*—Liver Cancer; Hepatocellular Carcinoma (HCC); Combined Ensemble Model (CEM); RESNET50; Extreme Gradient Boosting (EGB); Recurrent Neural Network (RNN)

I. INTRODUCTION

Cancer is a most complex diseases characterized by unrestricted cell growth and division in the body [1]. It is a significant public health concern worldwide and can affect almost any body part. Cells in the body normally grow, divide, and die in a controlled manner [2]. The body's genetic instructions tightly control this process. When this control is disrupted, cells can divide and grow uncontrollably, forming a tissue mass called a tumor. Tumors of two types, such as benign or malignant, Benign is non-cancerous, which is not more dangerous than malignant. Malignant is more dangerous because it is cancerous and spreads very quickly to all the body parts [3] [4]. The process of converting healthy cells into cancerous cells is known as carcinogenesis. Usually, it involves DNA alterations in the cell. These alterations can be brought on by a genetic predisposition, viral infections, to carcinogens (such as tobacco smoke or certain chemicals). The kind and stage of a cancer diagnosis can have a significant impact on the symptoms. Common symptoms include sudden weight loss, exhaustion, pain, skin changes, chronic coughing or hoarseness, lumps or masses, and altered bowel or bladder habits [5] [6]. Physical examinations, imaging tests, and laboratory testing are commonly used to diagnose cancer. Effective therapy depends on early discovery.

Image processing is an essential domain in detecting and diagnosing liver cancer. These models assist medical professionals in early cancer detection and treatment planning by extracting meaningful information from CT scans, MRIs, or ultrasound images [7]. Medical imaging, blood tests, and sometimes tissue biopsy are used to detect liver cancer. Early detection is critical for successful treatment and outcomes. A complete medical history taking into account risk factors such as alcohol use, hepatitis infection, and family history. They will also conduct a physical exam to look for signs of liver abnormalities like enlargement or tenderness [8] [9]. Several tests are available to aid in detecting and diagnosing liver cancer cells in CT scan images [10] [11]. Deep Learning (DL) is essential in detecting complex cancer patterns in liver CT scan images. Fig. 1 shows the sample liver lesions present in CT scan images.

This paper introduced the pre-trained model, such as ResNet-50, extracts accurate features from CT scan samples. Transfer learning with pre-trained models can significantly improve the proposed model's performance, particularly for limited labeled data. Denoising techniques are used in many image processing techniques to process CT scan images. In conjunction with various denoising filters, this paper removes noise from input CT scan images. Gray-level run-length Matrix (GLRLM) and region-based features were used to improve feature extraction.

A. *Contributions of this Work*

1) By integrating the distinct models, CEM is usually higher in forecasting because it consists of many basic models. Every model used in this work offers benefits while working on the proposed approach.

2) Complex interactions between many clinical and genetic variables are frequently involved in identifying liver cancer. CEM can more accurately forecast outcomes by capturing these complex interactions by combining many modeling methodologies.

3) The proposed model uses the Pre-trained model RESNET50 to get the accurate cancer disease patterns in the given samples.

4) An interesting features are obtained by using the hybrid feature extraction (HFE) that helps to improve the performance of final outcomes.

II. Literature Survey

Kim et al. [12] proposed a one-sided ANOVA approach for extracting the feature set for accurate disease detection using a feature (aptamer) array. For 80 liver cancer patients and 310 healthy people, the proposed approach combined AI with 10-fold cross specifications verified by aptamer array response. The proposed ANOVA approach has an accuracy of about 93.6% for ten features, which is 3.51% higher than the single-way method. Ahmad et al. [13] proposed a new approach called DBN-DNN, which can fine-tune the proposed DNN approach. An advanced pre-processing technique improves performance by employing an active contour technique based on liver features that store memory and measure time. The evaluation result shows that the proposed approach's performance on test images achieved a Dice score of 95.34%, which is high, compared to existing models. Balagourouchetty et al. [14] developed a CAD system for diagnosing liver diseases. The proposed method uses an ensemble FCNet classifier to classify hepaticae lesions based on several significant factors obtained from GoogleNet-LReLU transfer learning approaches. The proposed approach is a fully connected layer that includes classification and extraction using the inception layer and is combined with the ReLU activation function. Finally, the variety is based on six different types of liver diseases, and it is highly accurate. Yamakawa et al. [15] developed a new model for detecting tumors in the liver. The proposed method combines CNN with VGGNet to classify the four types of tumors based on the affected regions. The dataset contains 988 images representing various cases. When combined with CADx, the proposed method predicts liver cancer tumors with an accuracy of 94.56%, which is a high detection rate. Aslam et al. [16] presented an integrated learning model that combines image processing techniques and deep learning (DL) approaches to detect early-stage liver cancer tumors. The proposed model also employs the ResUNet, the most advanced model, to achieve better results. The dataset includes 100 CT scan liver tumor images from various patients. Finally, the proposed approach's accuracy is around 99.67%, and its F1-score is 94.8%, which is high compared to other systems in this paper. Shukla et al. [17] presented the automated liver tumor detection model from MRI scan images. The proposed approach divides the concave surfaces combined with geodesic active contour. The author introduced the Cascaded Fully CNN approach to segment the tumor region from the input sample. The training process reduces the error rate for liver segmentation. The final liver tumor analysis for the proposed approach is to obtain 94.56% accuracy and 88.89 Sec for computation of liver analysis. Sanyal et al. [18] presented a new model for detecting NAFLD based on the stage of liver disease. The proposed approach provided clear information about the liver status and stage in the early stages of the disease. As a result, this approach offers the default disease information that aids in detecting and diagnosing NAFLD. Li et al. [19] investigated NAFLD using various methodologies. Zhou et al. [20] proposed NAFLD for the detection of liver cancer. The author discussed about various models that helps to diagnose the cancer cells in liver. Marengo et al. [21] presented a new model for detecting HCC, a type of common liver cancer. Other factors, such as type 2 diabetes, NAFLD, and obesity, contribute to the rapid growth of HCC. It is a rapidly spreading cancer in the general population that should be detected in its early stages. The author discussed several techniques and methods for treating HCC and devised a limited solution. Sun et al. [22] talked about a variety of liver diseases. The author concentrated on detecting obesity-related health issues and their consequences. According to epidemiological studies, obesity is the root cause of various cancers. Obesity is strongly linked to other liver diseases such as NAFLD, NASH, and cancer. Kwon et al. [23] introduced a method for segmenting liver CT scan images using DL. The author wishes to identify additional factors influencing liver cancers based on human activities and habits. Manjunath et al. [24] presented a DL approach for detecting liver disease based on tumors growth. The tumor images are collected online and classified into Metastasis and Cholangiocarcinoma. The proposed approach gets better accuracy with 97.89% and a dice score of 98.23%. Lakshmipriya et al. [25] compared various DL algorithms based on classification, segmentation, and medical details of liver diseases. The author discussed different DL algorithms and found new challenges from the existing algorithms. Piyush Kumar Shukla et al. [26] presented an automated liver disease detection system that finds the tumors and lesions in the MRI images belonging to abdomen images that are gathered from 3D-related abhorrent and shape-based model results. The proposed approach combined with geodesic active contour analysis to find the different liver regions in the body. Finally, the training approach reduces the error rate by using the CFCNs to detect the segmented tumor image. In the final step, the segmentation approach obtained a tumor detection accuracy of 94.67% with a computation time of 17 seconds for one photo. The DL technique, which identifies liver tumors from CT scan pictures, was first presented by Heng Zhang et al. [27]. The CNN model was employed to segment CT scan images. Based on experimental results, comparisons between several segmentation approaches are presented. The automated KMC method, which offers a region-based growth strategy to locate the tumor region and display tumor grades, was proposed by Liping Liu et al. [28]. The deficiencies belong to blood vessels in the portal venous phase (PVP) based on the poor density of the liver CT scan pictures. In the last stage, patients with 26.67% having low blood deposition effect and 54.34% having high blood were discovered. Nayantara et al. [29] introduced the effective segmentation that detects liver diseases accurately on CT scan images. The author analyzed several DL algorithms that find liver diseases accurately. Zhang et al. [30] presented the diagnosis of liver diseases using Dl algorithms. Mubashir Ahmad et al. [31] developed the patch-based DL algorithm that segments the liver CT scan images using SAE. The proposed approach processes every pixel of the image and finds the accurate patches of initialize the liver disease-affected regions. The preprocessing method improved the images and created overlapping patches from each one, which were then fed into the SAE to extract features. In the last step, the classification is used to classify the affected regions based on the feature extraction. The proposed approach obtained the dice score similarity up to 97.23%, which shows high accuracy. Manoj Kumar et al. [32] proposed a comparative study that finds the overall liver disease patients based on three stages. The preprocessing technique min-max normalization is applied, and in the second step, the PSO feature extraction is used to extract the significant data from the input CT scan images and improve the disease detection rate. Li et al. [33] proposed a novel approach that detects liver cancer from liver CT scan images. Two datasets, such as MICCAI 2017 and 3DIRCADb data sets, are used for evaluation. The proposed approach focused on detecting the cancer-affected regions by using segmentation with the FCNN model and UNet (H-DenseUNet) that effectively extract the hybrid feature fusion layer. The comparison between several algorithms shows the proposed approach obtains good outcomes. Amita Das et al. [34] introduced the WGDL approach for detecting cancer lesions using CT scan images. The input CT scan images are separated using watershed segmentation and GMM to divide the cancer lesion. Finally, the DNN is used for classification based on segmentation outcomes. Anandan et al. [35] presented the enhanced filtering approach called NMADF that helps filter the input CT scan images. The proposed approach uses the two-fold segmentation that segments the liver cancer images. The canny edge detection approach is used as a preprocessing technique—finally; the improved DNN approach is used to classify liver cancer images. The results show the better performance of the proposed approach compared with existing models.

A. Limitations of Existing Models

1) The existing model requires massive training data to solve the sample imbalance.

2) There needs to be more accurate classification of normal and cancerous samples.

3) The existing models require high-quality images to detect accurate results.

4) There must be more issues in finding the accurate affected region in the given sample.

III. Dataset Description

The dataset was obtained from Kaggle and contains CT scan images related to contrast and patient age. The default viewpoint is to find various image textures tested for analyzing trends in CT scan images and statistical patterns. It features strongly correlated with these traits and possibly builds simple tools for automatically classifying these images when they have been misclassified. The total images used for training is 500 and testing is 500 CT scan liver images. The size of image in dataset is 500 x 500 width and height and size is 5-6 MB. The sample datasets with different types of images are shown in Fig. 1. All the images are in same size and pixel rate.

A. RESNET50 (Pre-Trained Model)

A common and practical approach in medical image analysis is the ResNet-50 model for cancer cell detection. ResNet-50 is deep convolutional neural network (DCNN) architecture with great success in image classification and object detection. When used to detect cancer cells, it can aid in identifying and classifying cancerous cells in medical images such as histopathology slides or radiological scans. ResNet-50 comprises 50 Convolutional layers connected by skip connections (residual blocks). The ResNet-50 weights were fine-tuned on a liver cancer cell dataset using popular deep-learning libraries such as TensorFlow. On the training data, train the ResNet-50 model with appropriate loss functions such as binary cross-entropy or focal loss for binary classification (cancerous or non-cancerous). To attain the highest validation set performance, track and modify hyper parameters like learning rate and batch size. To avoid over-fitting, techniques such as early stopping are used. If necessary, the post-process approach is used to predict to remove noise or refine the detected cancerous regions. The overall architecture of RESNET 50 is explained in Fig. 3. The input image and final output is obtained after processing all layers.

B. Pre-processing and Noise Removal

Pre-processing is essential in removing noise from input liver CT scan images. This paper combines an advanced pre-processing technique with Iterative Reconstruction (IR) and Anisotropic Diffusion (AD). It is beneficial for removing noise and improving image quality and diagnostic accuracy in CT (computed tomography) scan images. Various noise reduction techniques can be used depending on the specific noise characteristics and the image processing goals. Fig. 2 and Fig. 5 shows the input and output of the image selected from dataset.

C. Iterative Reconstruction (IR)

Iterative reconstruction is a computational technique used in medical imaging to improve image quality and reduce radiation exposure, particularly in CT (computed tomography) scans. It is an alternative to traditional filtered back projection (FBP). It is a simpler and faster method but may result in lower-quality images, mainly when data is limited, or measurements are noisy. Iterative reconstruction algorithms can address these issues by refining the vision iteratively based on the acquired data and a mathematical model of the imaging process. A CT scanner captures a series of X-ray projections as it rotates around the patient. These projections are different angles of CT-Scan attenuation through the patient's body. The iterative reconstruction process estimates the patient's internal structures, usually a simple or uniform image. The initial image generates CT-Scan projections as if the image were actual. This step uses a mathematical model that accounts for the CT-Scan attenuation properties of the tissues being imaged.

x: The true underlying image we want to reconstruct.

y: The acquired data (e.g., projection data in CT imaging).

R: The reconstruction operator that maps the image x to the acquired data y.

ϵ: The noise or error in the data.

The iterative reconstruction process can be represented mathematically using the following equation:

$$y = R(x) + \in$$

The goal is to find the best estimate x_k of the true image x iteratively minimizing the variance among the acquired and estimated data $R(x_k)$. this is typically done by solving the optimization issue at every iteration:

$$x_{k+1} = \mathrm{argmin}_x\{||y - R(x)||^2 + \leftthreetimes \Phi(x)\}$$

$||y - R(x)||^2$Represents the data fidelity term, $\Phi(x)$ is a regularization term that enforces some desired properties on the reconstructed image, such as smoothness or sparsity.

$\leftthreetimes$ is a regularization parameter that controls the trade-off between data fidelity and regularization.

D. Anisotropic Diffusion (AD)

Anisotropic Diffusion (AD) is a method for edge-preserving smoothing in image processing. When used to enhance or denoise photos while maintaining structural integrity, it is especially helpful. AD can be used in the context of medical imaging to enhance the visibility of pertinent features, such as scans showing malignancy. Anisotropic diffusion is based on the principle of performing diffusion in a way that is less noticeable in homogenous regions and more evident along the image's borders. This reduces noise while maintaining significant edges and structures.

The AD equation is represented as:

$$\frac{\partial I}{\partial t} = \nabla.(c(||\nabla I||)\nabla I)$$

I is the image intensity

∇ is the gradient operator

$||\nabla I||$ is the magnitude of the gradient,

$c(||\nabla I||)$ is the diffusion coefficient.

t is the time.

Based on the gradient's magnitude, the diffusion coefficient $c(||\nabla I||)$ is a function that establishes the appropriate amount of diffusion at each location. The role that is applicable as:

$$c(||\nabla I||) = e^{-(\frac{||\nabla I||^2}{K^2})}$$

The amount of diffusion is controlled by the parameter K in this case. Greater diffusion is permitted by smaller K values, while greater K values better maintain edges. Iteratively solving the equation over the image is done until the desired degree of smoothing is attained. The goal of the procedure is to maintain edges and fine structures while smoothing the image more over homogeneous areas. Anisotropic diffusion can be used to improve the visibility of significant characteristics in cancer images, which will facilitate medical experts' analysis and interpretation of the images.

E. Gray-Level Run-Length Matrix (GLRLM)

A popular texture analysis technique in medical image processing is the GLRLM. CT scan images are analyzed for a variety of purposes, including cancer detection. GLRLM provides texture pattern information by quantifying the distribution of grey-level runs in an image. The GLRLM describes the correlations between pixel intensities along various directions and is commonly obtained from the co-occurrence matrix. Features that characterize an image's texture can be extracted using the GLRLM and used for classification or other analysis purposes.

1) Run-Length Matrix (RLM): The RLM $P(a, b)$ is calculated by counting the number of consecutive pixels with intensity a and length b in a specified direction. Let N be the number of gray levels.

$$P(a, b) = \sum_{x=1}^{N} \sum_{y=1}^{M} \delta(I(x, y) = i \text{ and } R(x, y) = j)$$

Normalized Gray-Level Run-Length Matrix (NGLRLM):

Normalize the RLM to obtain the NGLRLM:

$$P_{norm}(a, b) = \frac{P(a, b)}{\sum_{x=1}^{N} \sum_{y=1}^{M} P(a, b)}$$

2) Gray-Level Run-Length Matrix (GLRLM) Features: Several statistical measures can be computed from the GLRLM to extract features. Some of significant features are given below:

Short Run Emphasis (SRE):

$$SRE = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} \frac{P(a,b)}{j^2}}{\sum_{i=1}^{N} \sum_{j=1}^{M} P(a, b)}$$

Long Run Emphasis (LRE):

$$LRE = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} P(a, b) \cdot j^2}{\sum_{i=1}^{N} \sum_{j=1}^{M} P(a, b)}$$

Gray-Level Non-Uniformity (GLN):

$$\sum_{i=1}^{N} \sum_{j=1}^{M} P(a, b)^2$$

Run Length Non-Uniformity (RLN):

$$\sum_{i=1}^{N} \sum_{j=1}^{M} P(a, b)^2$$

F. U-Net Architecture

It is used for segmentation of cancer cells in given dataset images. The architecture consists of a contracting path, a bottleneck, and an expansive path.

1) Contracting path: It is responsible for capturing context and reducing the spatial resolution of the input image.

$$\mathrm{Conv}(x, \mathrm{filters}, \mathrm{kernel}_{size}, \mathrm{activation} =' \mathrm{relu}', \mathrm{padding} \\ = '\mathrm{same}'$$

x is the input tensor.

filters is the number of filters in the convolutional layer.

kernel_{size} is the size of the convolutional kernel.

activation is the activation function, typically ReLU.

padding is set to 'same' to maintain the spatial dimensions.

$$\mathrm{maxpool}(\mathrm{x}, \mathrm{pool}_{\mathrm{size}}, \mathrm{strides}$$

where,

$\mathrm{pool}_{\mathrm{size}}$ is the size of pooling window.

Strides is the stride of the pooling operation.

2) Skip connections: In order to concatenate feature mappings from the contracting path to the appropriate layer in the expansive path, the U-Net design uses skip connections.

$$\mathrm{concatenate}(\mathrm{conv}_{\mathrm{block}_{\mathrm{output}}}, \mathrm{corresponding}_{\mathrm{conv}_{\mathrm{block}_{\mathrm{output}}}})$$

3) Output layer: It is also a convolutional layer with a sigmoid activation function, producing the final segmentation map.

$$\mathrm{conv}(\mathrm{x}, 1, 1, \mathrm{activation} =' \mathrm{sigmoid}')$$

where:

1 is the number of filters (assuming binary segmentation, i.e., cancer cell or background).

1 x 1 convolutional kernel is used.

IV. Extreme Gradient Boosting (XGBoost)

In this paper, the Extreme Gradient Boosting (XGBoost) approach is used for the classification of input cancer and non-cancer images. Usually, a binary classification model with the target variable being a binary value indicating whether or not a patient has liver cancer is used to identify liver cancer using XGBoost. The two components of the XGBoost objective function are the regularization term, which penalizes the model's complexity in order to prevent over fitting, and the loss function, which calculates the difference between the true and predicted values.

$$\mathrm{Objective} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{loss}(\mathrm{y}_{\mathrm{i}}, \hat{\mathrm{y}}_{\mathrm{i}}) + \sum_{\mathrm{k}=1}^{\mathrm{K}} \Omega\,(\mathrm{f}_{\mathrm{k}})$$

n -total training samples

y_{i} -True table for i^{th} sample.

$\hat{\mathrm{y}}_{\mathrm{i}}$ -predicted output for i^{th} sample.

K- Total trees ensemble.

$\Omega(f_k)$ Regularization term for the k^{th} tree.

1) Loss Function: In this scenario, the loss function which is used for classification of cancer images is logistic loss:

$$\mathrm{loss}(\mathrm{y}_{\mathrm{i}}, \hat{\mathrm{y}}_{\mathrm{i}}) = -[y_i \log(\hat{y}_i) + (1 - \mathrm{y}_{\mathrm{i}}) \log(1 - \hat{y}_i)]$$

y_{i} is the true label.

$\hat{\mathrm{y}}_{\mathrm{i}}$ Predicted probability of class 1.

2) Regularization term: These terms are used by XGBoost to regulate the total model's complexity as well as the complexity of each individual tree. The regularization term for the k^{th} tree is a sum of the leaf scores:

$$\Omega(\mathrm{f}_{\mathrm{k}}) = \gamma\mathrm{T} + \frac{1}{2} \curlywedge \sum_{\mathrm{j}=1}^{\mathrm{T}} \mathrm{w}_{\mathrm{j}}^{2}$$

T total leaves in the tree.

w_j score associated with the j-th leaf.

γ and $\curlywedge$ Regularization parameters.

3) Tree Building Process: XGBoost builds trees in an additive manner, where each new tree is trained to correct the errors of the combined existing ensemble. The update at each step is given by:

$$\hat{\mathrm{y}}_{\mathrm{i}}^{(\mathrm{t}+1)} = \hat{\mathrm{y}}_{\mathrm{i}}^{(\mathrm{t})} + \eta \cdot \mathrm{f}_{\mathrm{t}}(\mathrm{x}_{\mathrm{i}})$$

The final equation classifies the input liver sample as tumor affected or not. The final architecture is given in Fig. 4 with step-by step approaches used to obtain the better output.

V. Performance Metrics

This section focuses mainly on showing the effectiveness of the proposed approach based on the outcomes. The performance metrics are obtained by using the proposed approach. The count values are obtained by the proposed classification approach. XGBoost is the classification model implemented by using the Python language with potential libraries. There are several libraries that help provide accurate results with the particular libraries. The performance is measured by using the following metrics. The count values are measured from the proposed approach. Fig. 6 shows the attributes of performance measures based on confusion matrix.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$$

$$\mathrm{F1-Score} = 2 * \frac{(\mathrm{Precision} * \mathrm{Recall})}{(\mathrm{Precision} + \mathrm{Recall})}$$

A. Experimental Results

This section mainly focused on analyzing the performance of the proposed approach is compared with several existing models. This section focused on providing the analysis of every parameter that shows the huge impact on output. It includes the training and testing loss and training and testing accuracy for the given pre-trained model. Also, this consists of comparative performances of several existing algorithms compared with the proposed algorithm.

The training loss measures the performance of model on training data. It initializes the error between the estimated output and original output at the time of training phase. In this paper, the loss is minimized by updating the model parameters by using several optimization algorithms. Testing loss mainly generalizes the model performance on new and unknown data. It is evaluated on a different dataset that the model has not seen during training. The proposed model shows the better performance by showing the balanced outcomes. The performance metrics based on the reduced testing and training loss are displayed in Fig. 7. It shows the proportion of successfully predicted instances to all instances in the dataset and is commonly stated as a percentage. There are two main types of accuracy: training and testing accuracy. Training accuracy gives an indication of how well the model has learned the training data. High training accuracy does not, however, guarantee that the model will perform well when applied to novel or unidentified data. The model's accuracy on a different dataset that it was not exposed to during training is known as testing accuracy. Since testing accuracy shows how well the model is likely to function on unknown data, it is a more significant parameter. Fig. 8 shows the performance of training phase testing phase.

Table I shows the performance of ML algorithms without using any ensemble techniques or pre-trained models. It is the classification models obtained by the implementation of ML algorithms. Fig. 9 shows the comparisons between ML algorithms.

B. *Figures and Tables*

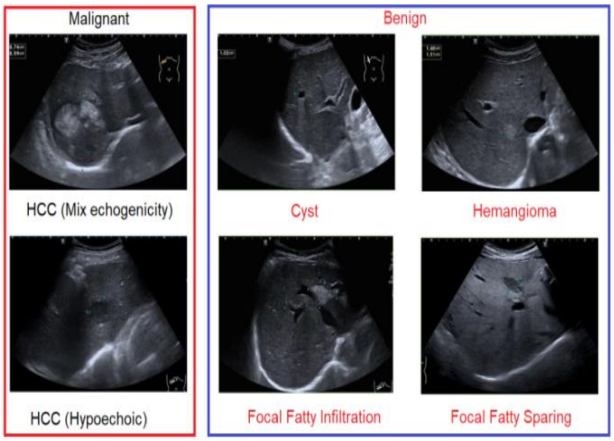

Fig. 1. Sample liver lesions.

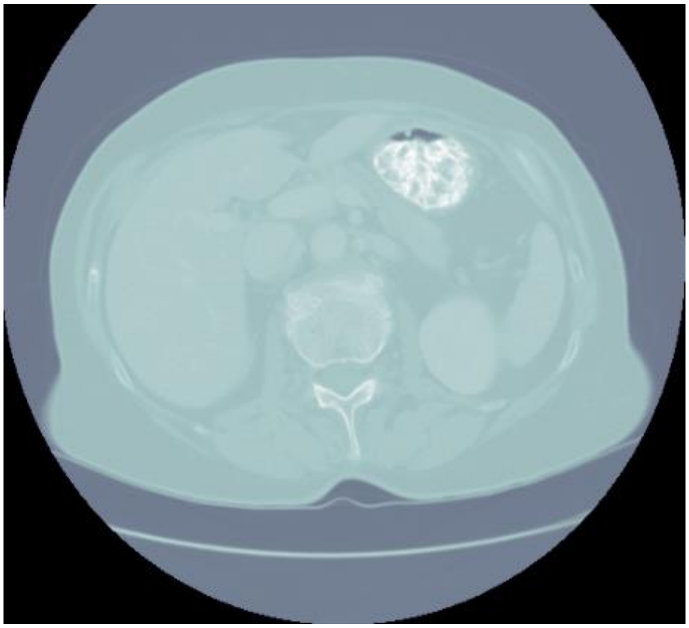

Fig. 2. Liver cancer CT scan image from dataset.

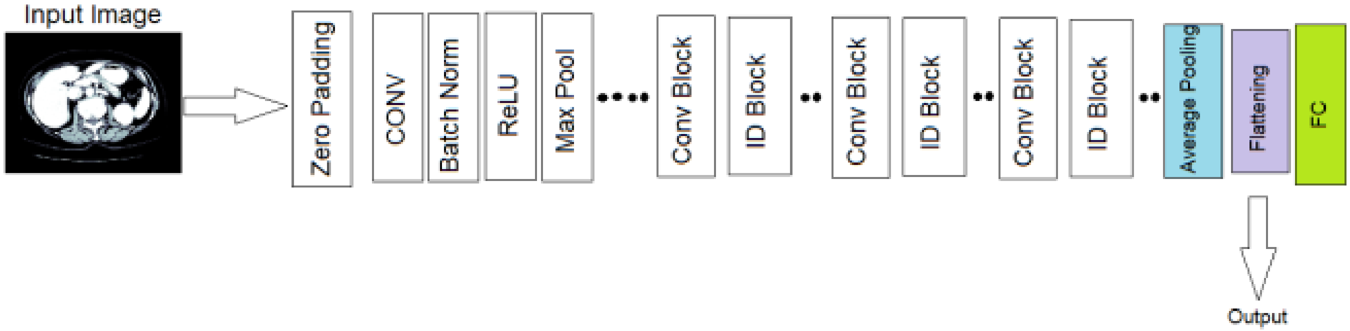

Fig. 3. Architecture of RESNET50.

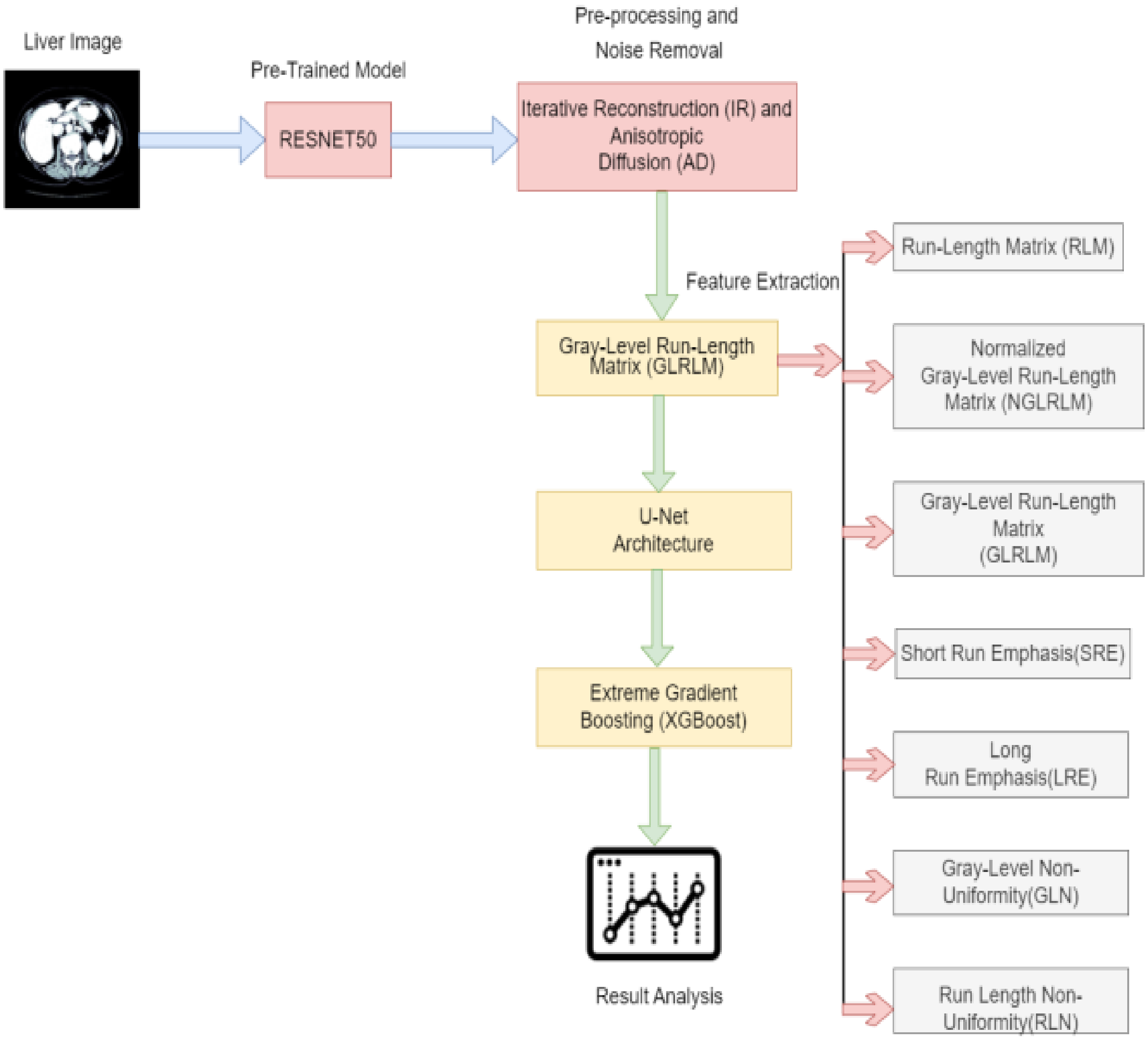

Fig. 4. The proposed architecture.

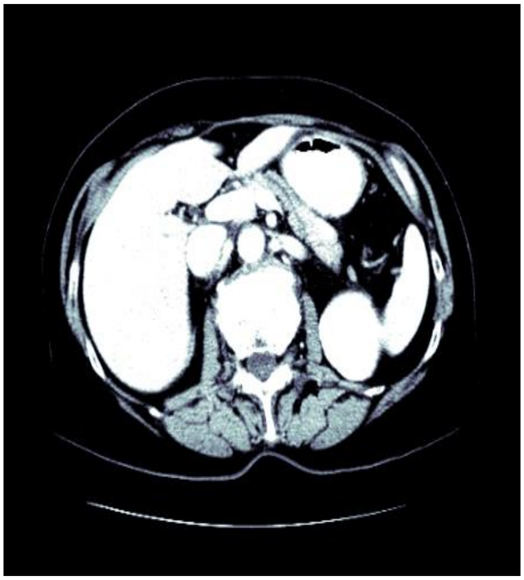

Fig. 5. The output after the Preprocessing technique.

True Positive(TP)	False Positive(FP)
False Negative(FN)	True Negative(TN)

Fig. 6. Confusion matrix.

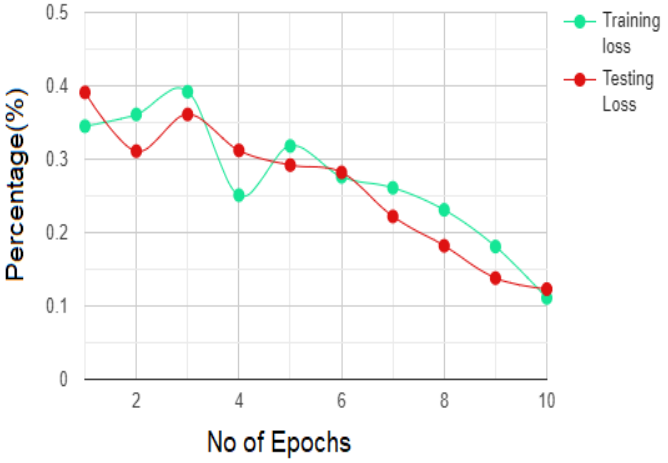

Fig. 7. Performance in terms of proposed pre-trained model.

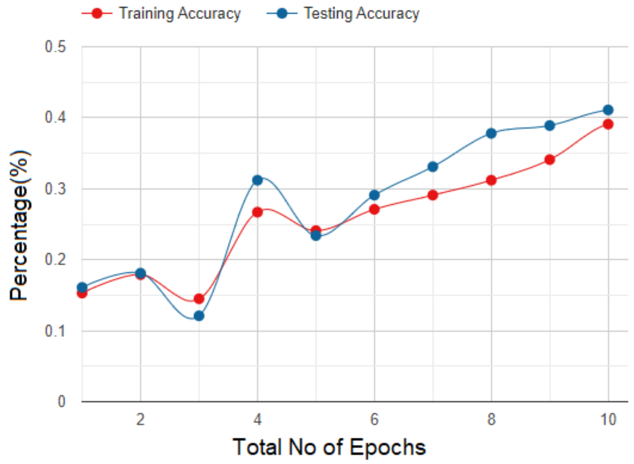

Fig. 8. The performance of pre-trained model in terms of training and testing accuracy.

TABLE I. THE PERFORMANCE OF VARIOUS ML MODELS

Parameters	Random Forest (RF)	CNN	XGBoost
Precision	73.23	76.23	86.56
Accuracy	74.53	80.34	88.12
Recall	75.12	81.23	89.23
Specificity	71.23	83.56	90.34
F1-Score	73.34	84.23	91.34

Table I shows the obtained results that are obtained by using existing algorithms such as RF, CNN and XGBoost. Among all these algorithms the XGBoost gained the better classification results compared with existing approaches. The traditional XGBoost obtained the high performance in terms of accuracy of 88.12%, precision of 86.56%, recall of 89.23, Specificity of 90.23 and F1-Score of 91.34.

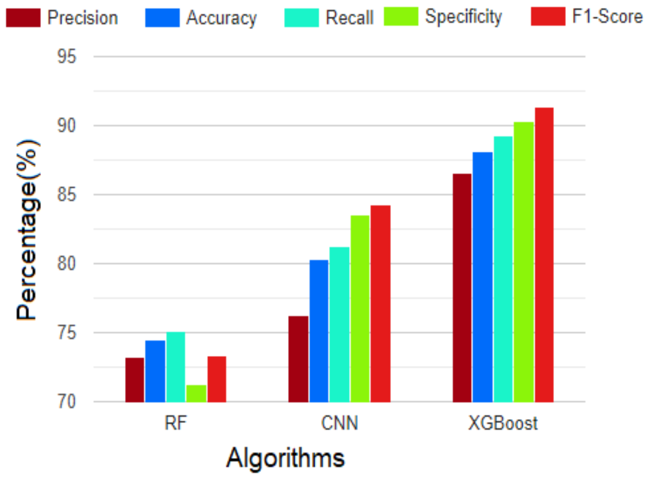

Fig. 9. The comparative performances of various ML algorithms.

TABLE II. THE OVERALL PERFORMANCE OF ALL THE ADVANCED ALGORITHMS THAT EVERY ALGORITHM IS COMBINED WITH VARIOUS PREPROCESSING AND FEATURE EXTRACTION TECHNIQUES

Parameters	Random Forest (RF)	CNN	Combined Ensemble model (CEM)
Precision	83.45	88.23	97.81
Accuracy	84.23	89.34	98.48
Recall	85.12	90.23	98.65
Specificity	81.23	90.56	98.45
F1-Score	82.87	91.23	98.19

Table II shows the comparison between traditional and Ensemble Algorithms that shows the high performance in terms of various parameters. The proposed CEM is the ensemble algorithm that combines with the U-Net and XGBoost. It achieved the high accuracy of 98.48% based on correctly classified outcomes. The remaining parameters are also shows the high rate. Finally, Fig. 10 shows the overall performances of existing and proposed algorithms.

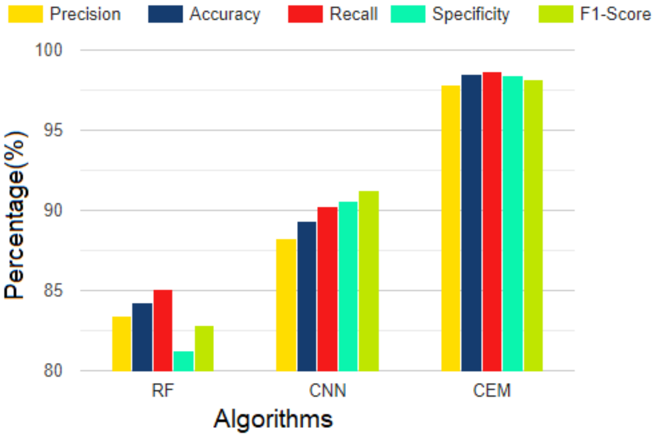

Fig. 10. The overall performances of existing and latest algorithms.

VI. Conclusion

In this work, we looked into the use of a Combined Ensemble Model (CEM) in liver cancer diagnosis. Utilizing each model's unique characteristics to improve overall forecast accuracy and reliability was the main goal. Our results show that the CEM technique has the potential to enhance liver cancer diagnostic skills. The ensemble model performed better than the individual models alone. It was created by combining many algorithms, such as [list of individual models]. By combining several algorithms, the constraints of using a single model were effectively mitigated and a more reliable and accurate prediction of liver cancer was made. Furthermore, the CEM demonstrated enhanced generalization capabilities, suggesting its potential applicability to diverse patient populations and datasets. The ensemble approach not only improved sensitivity and specificity but also provided a more comprehensive understanding of the complex patterns within the data. While the CEM outperformed individual models, it is crucial to acknowledge the importance of continuous refinement and optimization. Future work should focus on fine-tuning the ensemble model, exploring additional algorithms, and incorporating new features to further enhance its diagnostic capabilities. The implications of our study extend beyond the realm of liver cancer diagnosis. The success of the CEM approach highlights the value of ensemble techniques in medical decision-making, emphasizing the significance of model diversity and collaboration. This research contributes to the growing body of evidence supporting the use of ensemble models in healthcare applications. Finally, the Combined Ensemble Model presents a promising avenue for improving the accuracy and reliability of liver cancer diagnosis. As we move forward, it is essential to continue refining and validating the model on larger and more diverse datasets, ultimately paving the way for its potential integration into clinical practice.

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Automatic Dust Reduction System: An IoT Intervention for Air quality

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Abstract—**Air quality is of great importance due to its direct impact on the environment, human health, and quality of life. It could be affected negatively by the presence of dust particles in the atmosphere. Thus, it is vital to purify air from dust and mitigate its impact on air quality. In this regard, dust sensors play a vital role in monitoring and measuring airborne dust particles. They utilize various techniques, such as optical scattering, to detect and quantify the concentration of dust in the air. Microcontrollers are powerful and versatile devices, which have been widely used in many Internet of Things (IoT) applications. They process the collected data from sensors and react accordingly by controlling the operation of IoT devices. Accordingly, the primary goal of this paper is to develop a model for reducing the amount of dust and other particulates in the air to improve its quality. In addition to the microcontroller, which controls the overall operation of the proposed model, two other main components are utilized: a sensor and a sprinkler. The results of the model have shown that it can successfully reduce the dust concentration and suppress the dust intensity to less than 0.1%. The result concluded that the proposed model achieved its primary goals by integrating sensors and sprinkler into an intelligent dust removal model.**

Keywords—Dust Suppression; dust elimination; digital dust sensor; humidifier; dust intensity

I. Introduction

Because oxygen is supplied to our lungs, blood, and other organs through the air we breathe, it crucial for it to be as pure as possible to ensure a healthy life for humans. A vital component of environmental health is air quality. One of the biggest environmental hazards to human health is air pollution. As of 2019, 99% of people on Earth reside in places where air quality standards set by the World Health Organization (WHO) were not achieved. Each year, the poor air quality results in millions of deaths. Globally, ambient (outdoor) air quality is thought to have contributed to 4.2 million preventable deaths in 2019 [1, 10]. Surprisingly, multiple WHO's studies reveal that indoor air quality is five to ten times worse than outside air quality, especially in urban regions. The environment and human health are seriously threatened by air pollution, which is brought on by a variety of pollutants, including dust particles in the atmosphere [1, 3].

Poor air quality has a negative impact on the quality of life for individuals. Air pollutants have the potential to cause irritation. Many studies have demonstrated the link between specific air pollutants and lung cancer as well as respiratory ailments. The quality of the air both indoors and outdoors is vital. Common outdoor air contaminants include particulate matter, allergens, and ground-level ozone. Common indoor air contaminants include mold, radon, secondhand smoke, and dust [8].

Dust particles in the air are one of the main causes of air pollution [7] that could cause serious health hazards to humans. These particles can come from natural processes including wind erosion, vehicles emissions, construction sites, and industrial activity. High dust exposure can cause allergies, respiratory disorders, and other health concerns [4]. The issue with airborne dust is caused by the presence of rock dust in the atmosphere. Pneumonia is a potentially dangerous occupational lung illness that can be brought on by this dust. Statistics show that there are about 500 new cases of pneumonia detected yearly, which suggests that more work needs to be done to treat lung cancer and pneumonia [9].

In semi-arid environment, sandstorms frequently occur, especially in the summer. These sandstorms, which occur when strong winds swirl sand about and propel it into the air, may make it difficult for people to see far, and they also make driving more dangerous. The difficulty for drivers to spot other vehicles is a hazardous consequence, which raises the chances of accidents. Furthermore, breathing in dust might be harmful when traveling or working in factories that produce construction waste [2, 11, and 12].

In order to establish a sustainable ecosystem, it is essential to develop a model aimed at reducing the concentration of dust in the atmosphere. To lessen the severity of the dust and enhance the quality of the air, this study suggests a prototype that can be used to detect and reduce dust in the atmosphere. Thus, the goal of the paper is to create a dust removal system that employs intelligent control and hardware components to effectively minimize airborne dust particles.

Dust sensors greatly aid the monitoring and measurement of airborne dust particles. They use various techniques, such as optical scattering, to identify and measure the amount of dust in the atmosphere. Real-time data from these sensors makes it possible to evaluate the quality of the air and identify any possible health hazards. Therefore, the proposed model uses a dust sensor to continuously monitor dust levels in the air and start the necessary dust removal activities [5].

ESP32 microcontrollers are powerful and adaptable microcontrollers, which have been extensively utilized in Internet of Things (IoT) applications. Wi-Fi and Bluetooth are only two of the many communication capabilities provided by these controllers. They also have the processing capacity to manage sensor data and operate auxiliary devices. As the central nervous system of the dust removal system, the ESP32 microcontroller facilitates data processing, communication among hardware elements, and decision-making based on gathered sensor data. Existing methods of dust removal typically involve passive techniques such as air filters and ventilation systems [13]. While these methods can provide some level of dust reduction, they often have limitations in terms of efficiency, scalability, and real-time monitoring. Thus, the proposed model aims to overcome these limitations by developing an active and responsive system that can detect elevated dust levels and initiate immediate dust suppression measures [6, 8].

The remaining of this paper is organized as follows. Section II discusses the related work, Section III illustrates the methodology. Section IV presents the dust mitigation prototype. Section V presents experimental setup of the proposed model and results. Section VI presents the discussion and conclusion.

II. Related Work

According to the Energy Progress Report published in 2022 by the International Energy Agency (IEA), International Renewable Energy Agency (IRENA), World Bank, and World Health Organization (WHO), the United Nations Sustainable Development Goals (SDGs), which include improving air quality, are largely dependent on sustainable energy solutions [1]. The report evaluates the state of the world's efforts to achieve SDG 7, which is to guarantee that everyone has access to modern, affordable, dependable, and sustainable energy by 2030. It assesses advancements in energy efficiency, renewable energy, and the availability of clean cooking fuels and electricity. The proposed dust reduction system, which uses information technology to reduce air pollution, is in line with these objectives. The report offers a comprehensive discussion about the need to design creative solutions for monitoring air and reducing air pollution.

An annual report on the primary technical and natural dangers associated with hard coal mining has been made available [14], with a focus on the industry's need for efficient dust control. This report lists several coal mining dust emission sources, such as loading, blasting, drilling, and transportation. It also covers a number of dust control techniques used in the sector, including ventilation, water spraying, and the application of personal protection equipment. It is crucial to continuously monitor and control dust levels in order to lower the hazards related to dust exposure.

Controlling dust concentration in a hard coal mine processing plant's workplace was the subject of another investigation, which found that the spraying system, called New Environmentally Friendly and Efficient Pulverization Technology for Underground Mining (NEPTUN), significantly decreased dust levels [3]. The researchers measured the dust concentration before and after installing the NEPTUN system at various workstations using a dual-channel laser dust monitor. The results of the investigation showed that the processing plant's dust concentrations were considerably lower because of the NEPTUN spraying system, which suppresses dust using high-pressure water spraying. The results also showed that larger nozzle diameters and higher water pressure enhanced the system's efficiency.

A comprehensive review of many types of sensors, their operational mechanisms, and their uses in a variety of industries, including biomedical engineering, automotive systems, and environmental monitoring, was provided in [15]. The study covered the most recent developments in sensor technology, including wireless sensor networks and the IoT, which make it possible to gather and interpret vast amounts of sensor data for sophisticated applications. Furthermore, an overview of the several kinds of sensors—physical, chemical, and biological—as well as their uses in a range of industries, including agriculture, health care, and environmental monitoring, were given [16]. This study underlined how crucial it is to choose the right sensors for a given application based on factors like sensitivity, specificity, and operating principles. This discussion of the different sensor technologies provided insightful information that was useful for the creation and incorporation of sensors in the proposed dust reduction system.

The authors in [17] described multisensory data fusion and filtering for vehicle’s safety systems, which provide insightful information for the integration of several sensors in the suggested dust reduction system. They presented a number of data fusion methods that may be used to integrate and merge data from many sensors in order to enhance system performance, including Bayesian networks, particle filtering, and Kalman filtering. Furthermore, it emphasized the significance of sensor fusion in vehicles’ applications, including autonomous vehicles and driver assistance systems, where it is necessary to integrate data from several sensors to produce precise and trustworthy information for decision-making. The study underlined how important it is to take sensor fusion techniques into account when developing the suggested dust reduction system since it is likely to need information from several sensors in order to monitor and regulate the dust levels.

The use of big data and IoT technology in air quality monitoring was examined in [18], which offered insightful information for the suggested dust reduction system. The authors suggested an IoT-based air quality monitoring system that gathered data in real time from air quality sensors placed around different areas. Big data analytics techniques were used to process the gathered data in order to find trends, patterns, and anomalies and produce insights that decision-makers could use. The adoption of IoT and big data technologies in air quality monitoring presents a number of potentials and problems, including data security, privacy, and system scalability, all of which were covered in this study. The study emphasized how IoT and big data technologies might provide continuous, real-time monitoring of air quality, which could be essential for the successful installation of the suggested dust reduction system.

An automated cleaning method for removing dust from solar PV modules was demonstrated in study [19]. They discovered that automated cleaning solutions can enhance the performance of solar panels and are more effective and efficient than hand cleaning. The proposed model's dust removal component may benefit from the knowledge gained from this investigation.

In study [20], a smart dry fog technology for controlling fugitive dust emissions was introduced. The system is composed of a dry fog generator, a control unit, and a network of sensors. A thorough analysis of dust suppression systems was given in [21], which also assessed in applying this technology in different industries as well as their limitations and effectiveness. The efficiency of several dust suppression techniques, including ventilation, chemical treatment, and water spraying, in reducing dust emissions from various sources was covered by the authors. They also emphasized the significance of taking into account the unique properties of dust particles, such as their size, shape, and moisture content, when choosing the best dust suppression methods. The paper stressed on the importance of continuously monitoring and controlling dust levels in order to guarantee efficient dust control. A further study put forth a framework for incorporating sensors into an IoT platform [22]. A methodical approach to sensor integration—which encompasses sensor selection, data collection, processing, fusion, and visualization—was put forth by the authors. The framework highlighted the factors that should be taken into account when choosing the right sensors for a certain application type. These factors include cost, accuracy, and dependability. The authors also covered the opportunities and difficulties of integrating sensors into IoT platforms, including system scalability, data security, and privacy [23]. In conclusion, previous studies have shown that there is still room to develop novel approaches with even higher precision than those used previously in order to reduce or suppress dust particles in the ambient air.

III. Methodology

The proposed prototype for dust reduction includes five key components which are, the dust sensor, ESP32 microcontroller, sprinkler controlled by a spray module, TFT screen, and water level sensor. These components work together in a coordinated manner to achieve the goal of dust removal.

The dust sensor is responsible for detecting and measuring the concentration of dust particles in the air. It uses a digital dust particle sensor that can identify air dust aerosols greater than 0.8 μm in diameter. The sensor continuously monitors the ambient air and provides real-time data on the dust concentration. The ESP32 microcontroller acts as the central control unit of the system. It receives data from the dust sensor and processes it to determine if the dust concentration exceeds a predefined threshold. When the threshold is exceeded, the microcontroller triggers the spray module to initiate the dust suppression process. The spray module is designed to release a fine mist or water spray into the air to effectively reduce the dust concentration. It is comprised of a pump, nozzles, and a plumbing system that distributes the water evenly. The microcontroller controls the activation of the spray module based on the inputs received from the dust sensor. The TFT (Thin Film Transistor) screen, with its 3.5-inch display, serves as the user interface of the system. It provides real-time visual feedback to users, displaying the current dust concentration level, water tank level, and other relevant information. The TFT screen enhances user interaction and allows for monitoring and control of the system's operation. To ensure proper functioning of the system, a water level sensor is integrated to monitor the water tank level. It accurately measures the water level and provides feedback to the microcontroller. This allows the system to optimize water usage and prevent interruptions in the dust removal process.

By integrating and coordinating the functions of the above discussed components: dust sensor, ESP32 microcontroller, spray module, TFT screen, and water level sensor, the proposed prototype creates an intelligent and responsive dust removal system. The cooperative functioning of these components ensures efficient and effective dust suppression, leading to improved air quality and a healthier environment.

A. *Proposed Model Architecture*

The software system architecture encompasses the design and structure of the software system components that enable the coordination and functionality of the hardware tools. It involves the implementation of various software modules and their interactions to achieve real-time dust monitoring, automatic dust suppression, and user interface capabilities. The components contribute to the overall software architecture are:-

- Firmware for ESP32:- The ESP32 microcontroller requires firmware that serves as the foundation of the system. This firmware includes the necessary drivers and libraries to interface with the hardware components, such as the dust sensor, water level sensor, TFT screen, and spray module. It also manages communication between the different components of the system using protocols, such as Wi-Fi and Bluetooth, to facilitate data exchange and connectivity.

- Dust Monitoring and Control: The software architecture incorporates two modules for dust monitoring and control. The dust monitoring module reads the data from the dust sensor in real-time and processes it to determine the current dust concentration. Based on predefined thresholds, the control module initiates actions to activate the spray module for dust suppression. These modules work together to continuously monitor the air quality and respond accordingly.

- User Interface: The user interface module provides a visual representation of the system's status and enables user interaction. It utilizes the TFT screen to display real-time information, including the dust concentration level and water tank level. The user interface module allows users to monitor the system, adjust settings, and view historical data. It provides a user-friendly and intuitive interface to enhance user experience and system control.

- Data Storage and Analysis: This module captures and stores relevant data, such as dust concentration readings, system status, and user settings. It enables historical data analysis, trend identification, and performance evaluation of the dust removal system.
- Communication and Connectivity: The software architecture system includes modules for communication and connectivity. These modules enable the system to transmit and receive data from external sources, such as remote monitoring systems or control interfaces. Communication protocols like Wi-Fi or Bluetooth are utilized to establish connections and exchange information with other devices or systems. This enables remote monitoring, control, and integration with larger networks or cloud-based platforms.

The software architecture of the system ensures the seamless integration of the various software components with the hardware tools. It enables real-time monitoring, automatic control, user interaction, data storage, and connectivity functionalities. Through a well-designed software architecture, the dust removal system can effectively detect elevated dust levels, initiate appropriate actions for dust suppression, provide visual feedback to users, and facilitate data analysis for system optimization and performance evaluation.

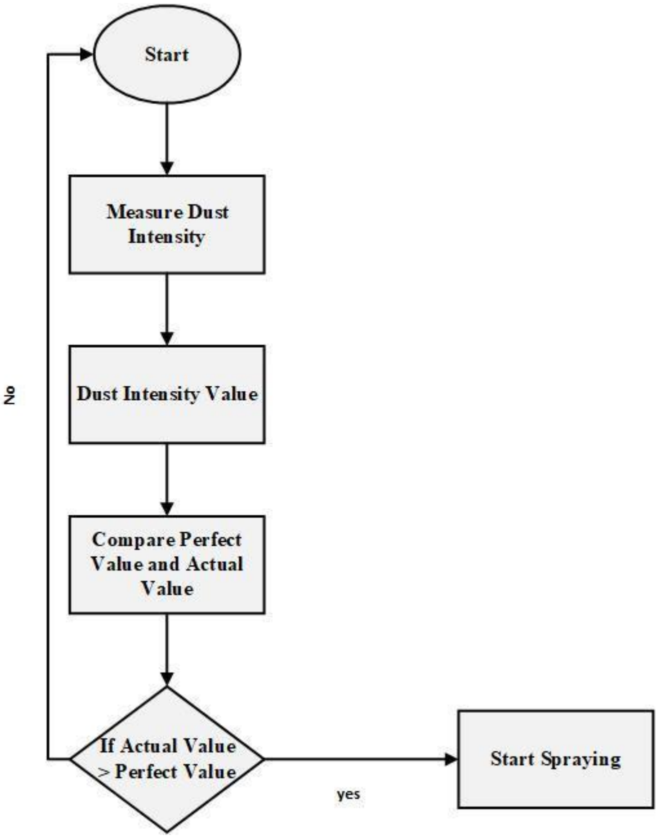

Start
Measure Dust Intensity
Dust Intensity Value
Compare Perfect Value and Actual Value
If Actual Value > Perfect Value
Start Spraying
yes
No

Fig. 1. Flowchart of the proposed system mechanism.

The flowchart in Fig. 1 represents a simplified process for an automatic dust reduction system. The purpose of this system is to measure the dust intensity in the environment and determine if it is necessary to start spraying to reduce the dust levels. The steps of this dust reduction system are as following:-

1) Start: The process begins by initializing the automatic dust reduction system.

2) Measure dust intensity: The system measures the current dust intensity in the environment using dust sensors.

3) Dust intensity value: The measured dust intensity value is obtained from the sensors.

4) Compare threshold value and actual value: The system compares the actual dust intensity value with a predefined (acceptable) value. This value represents the maximum of dust intensity level in the environment, where below this value no dust suppression action is needed. The system checks if the actual dust intensity is greater than the threshold value. If the actual value is greater than the threshold value, it indicates that the dust levels in the environment are too high and require intervention to mitigate the dust. If the actual value is less than the threshold value, the system returns to the "Measure dust intensity" step, and continue monitoring the dust levels in the environment.

5) Start spraying: If the actual dust intensity value is higher than the threshold value, the system initiates the spraying process to reduce dust levels in the environment. After spraying, the system returns to the "Measure dust intensity" step to reassess the dust levels and determine if additional spraying is necessary.

IV. DUST MITIGATION PROTOTYPE

In the proposed system, the ESP32 microcontroller serves as the central control unit, managing the TFT display, dust sensor, water level sensor, and spray module. The system is powered by a Li-ion battery, which is charged using a charger. A voltage booster is connected between the battery and the ESP32 to ensure a stable voltage supply for the microcontroller and its connected components. Fig. 2 illustrate the different components of the system and the connections between these components.

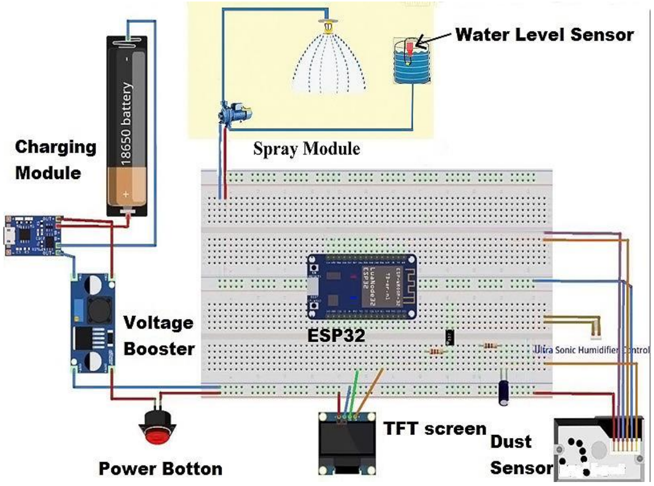
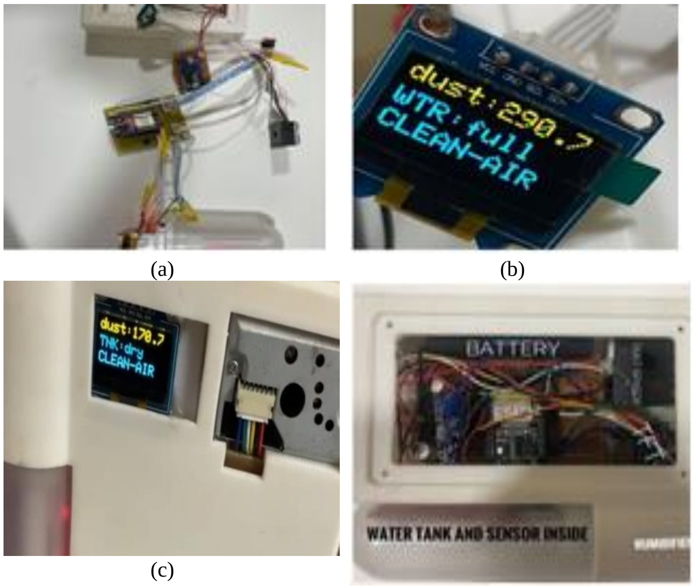


Fig. 2. Prototype components and connections.

In the followings, the role of each component is described:

- Charger Module and Li-ion battery: The charger provides power to the Li-ion battery, ensuring it remains charged and ready to supply energy to the system. The battery's role is to store energy and provide a stable power source for the entire system.
- Voltage booster: Connected between the Li-ion battery and the ESP32, the voltage booster steps up the battery's voltage to a suitable level for the microcontroller and its connected components. This ensures consistent performance and helps prevent under-voltage issues.
- ESP32 microcontroller: The ESP32 serves as the brain of the system, controlling and processing data from the sensors, managing the spray module, and displaying information on the TFT screen. It receives power from the voltage booster and communicates with each component through defined pin connections.
- TFT display: The TFT display is connected to the ESP32 and displays dust and water level readings, as well as warning messages when needed. It provides a user-friendly interface for monitoring the system's status.
- Dust sensor: The dust sensor is connected to the ESP32 through an analog input pin (A0). It detects dust levels in the environment and sends the readings to the microcontroller for processing. If the dust level exceeds the predefined threshold, the ESP32 activates the spray module.
- Water level sensor: The water level sensor is connected to the ESP32 through another analog input pin (A1). It measures the water level in the water tank used for the spray module. If the water level falls below a certain threshold, the ESP32 displays a warning message on the TFT screen.
- Spray module: Controlled by a servo motor connected to the ESP32, the spray module is responsible for releasing water to reduce dust levels when needed. The servo motor opens and closes the spray module based on commands from the ESP32.

The proposed dust reduction system is a cohesive unit that combines various sensors and components under the control of the ESP32 microcontroller. The system monitors dust and water levels, activating the spray module when necessary to mitigate dust levels, and alerts the user if the water level is low. The Li-ion battery supplies power, while the charger and voltage booster ensure stable and consistent performance (see Fig. 3).



(a) (b)

(c) (d)

Fig. 3. Prototype connections actual figure. (a) Prototype connections. (b) IoT-based water quality monitoring system, monitors dust and water levels. (c) Water sensor, alerts the user if the water level is low. (d) Li-ion battery supplies power.

V. EXPERIM ENTAL SETUP AND RESULTS

This section presents the test setup of the proposed prototype for dust mitigation. It includes the test setup, evaluation experiments, and the obtained results. The testing phase involved a comprehensive evaluation of the dust removal system to assess its functionality, performance, and effectiveness in reducing dust levels in the air. The testing phase aimed to validate the system's capabilities and ensure its reliable operation in real-world scenarios. The test was done in a controlled environment designed by the researcher. The system was implemented in a Plexiglass acrylic box measuring 15cm x 7cm x 20cm to simulate a controlled environment as seen in Fig. 4. Plexiglass acrylic is a transparent, lightweight, and durable material, making it suitable for creating a test chamber. The testing phase aimed to validate the system's capabilities and ensure its reliable operation in real-world scenarios. A controlled test environment was created, simulating different dust concentrations within the Plexiglass acrylic box. The test chamber was prepared with a calibrated dust source to generate consistent dust levels for evaluation. The system was calibrated and configured to establish baseline measurements and define the threshold for dust concentration. This calibration ensured accurate detection and appropriate response to elevated dust levels. Different evaluation setups were examined to test the proposed prototype:

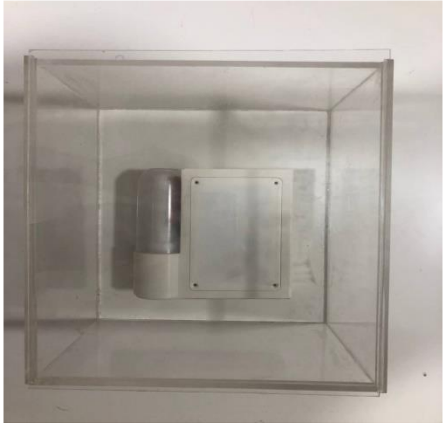


Fig. 4. Plexiglass acrylic box.

1) Evaluation No. 1: Evaluation Objective: Verification of the Activation and Efficiency of the Spray Module in Response to elevated dust levels. This Evaluation Procedure is as following:

- Initialize the Dust Reduction System.
- Set the initial dust concentration to 350 micrograms/m3.

Anticipated Outcome: The TFT display should accurately reflect the concentration of dust present in the immediate environment. With the initial concentration set at 350 micrograms/m3, the ESP32 microcontrollers expected to initiate the spray module, thus mitigating dust levels as shown in Table I.

TABLE I. THE PARAMETER OF EVALUATION NO. 1

parameter	values
The initial dust concentration	350 micrograms/m3
The final dust concentration	150 micrograms/m3
time	10 minutes

Documented Result: The TFT display displayed the correct initial dust concentration of 350 micrograms/m3. As anticipated, the ESP32microcontroller successfully initiated the spray module.

Evaluation status is successful, and the spray module effectively reduced the dust concentration from 350 micrograms/m3 to approximately 175 micrograms/m3 within a span of 10 minutes, which demonstrates a significant decrease of approximately 50% in dust levels.

2) Evaluation No. 2: Evaluation Objective: Examination of the Water Level Monitoring Mechanism and Warning Functionality Based on the Moisture Indicator. This Evaluation Procedure is as following:

- Initiate the Dust Reduction System.
- Deliberately allow the water reservoir to dry up, causing a change in the moisture indicator status from "moist" to "dry."

Anticipated Outcome: The TFT display should present the accurate status of the water level in the reservoir by displaying either "moist" or "dry." In the event that the water level descends to the "dry" status, a warning message "Low Water Level!" should be distinctly exhibited on the TFT display.

Documented Result: The TFT display successfully indicated the change in moisture status from "moist" to "dry." As soon as the moisture indicator switched to "dry," the ESP32 microcontroller successfully triggered the "Low Water Level!" warning message. The status of the evaluation is successful.

3) Evaluation No. 3: Evaluation Objective: Performance Analysis of the Dust Reduction System under Optimal Operational Conditions. The evaluation procedure is as shown:-

- Initiate the Dust Reduction System with the initial dust concentration set at 350 micrograms/m3 and the water level indicated as "moist."
- Monitor the system's performance in reducing dust levels.

Anticipated Outcome: The TFT display should correctly indicate both the dust concentration and the moisture status. With the initial dust concentration set at 350 micrograms/m3, the spray module should be initiated by the ESP32 microcontroller and effectively reduce dust levels.

Documented Result: The TFT display accurately demonstrated the dust concentration and moisture status. With the initial dust concentration set at 350 micrograms/m3, the spray module was successfully initiated by the ESP32 microcontroller, thereby reducing the dust levels. The status of the evaluation is successful.

The evaluation on effectiveness shows that the system exhibited high effectiveness as it reduced the dust concentration from 350 micrograms/m3 to around 175 micrograms/m3 within a 10-minute duration. This signifies a notable decrease of approximately 50% in dust concentration levels. Therefore, the system proves to be highly efficient in maintaining optimal dust levels in the environment.

The main difference between Evaluation No.1 and Evaluation No.3 lies in the specific objectives and conditions under which the Dust Reduction System is evaluated. Evaluation No. 1 concentrated on the system’s response to elevated dust levels and Evaluation No. 3 emphasized the overall performance under optimal conditions, including moisture status monitoring.

4) Evaluation No. 4: Evaluation Objective: Assess the Dust Reduction System's Performance in a Larger Test Environment (4m x 4m). Set up the Dust Reduction System in a controlled test environment designed by the researcher, a 4m x 4m room, simulating a larger workspace.

- Initiate the Dust Reduction System with the initial dust concentration set at 350 micrograms/m3 and the water level indicated as "moist."

- Monitor the system's performance in reducing dust levels in the larger test environment.

Anticipated Outcome: The TFT display should correctly indicate both the dust concentration and the moisture status. With the initial dust concentration set at 350 micrograms/m3, the spray module should be initiated by the ESP32 microcontroller and effectively reduce dust levels.

Documented Result: The TFT display accurately demonstrated the dust concentration and moisture status in the larger test environment. With the initial dust concentration set at 350 micrograms/m3, the spray module was initiated by the ESP32 microcontroller. However, the dust reduction performance was not as effective in the larger room compared to the smaller test environment.

The status of the evaluation is partially successful. Some technical issues were encountered during the test, which include uneven spray distribution and reduced spray coverage. These issues were attributed to the larger room size, which affected the spray module's ability to efficiently reduce dust levels throughout the entire space. Regarding the evaluation of the system's effectiveness in reducing the dust levels, the system has reduced the dust concentration from 350 micrograms/m3 to approximately 225 micrograms/m3 within a span of 10 minutes, which demonstrates a decrease of about 36% in dust levels.

In comparison to the previous evaluations conducted in the smaller test environment, the effectiveness of the system in the larger test environment was lower. This highlights the need for further optimization and adaptation of the system for larger spaces to achieve more efficient dust reduction. To enhance the system's effectiveness in larger environments, further research and development should focus on improving the spray module's coverage and distribution capabilities. This could involve modifying the nozzle design, optimizing the spray pressure, and incorporating additional spray units to ensure more uniform dust reduction throughout the entire space.

VI. Discussion

The proposed prototype for dust mitigation incorporated five components, which are a digital dust sensor, an ESP32 microcontroller, a water spray module, a TFT display, and a water level sensor to create a responsive and intelligent dust reduction system. The dust sensor monitored dust levels continuously, while the spray module suppressed dust when dust concentrations exceeded a pre-specified threshold. Together, all the system components have been utilized to reduce the environmental dust load.

The performance evaluation revealed that the combined dust sensor and sprinkler module system successfully reduced dust levels. In about 10 minutes, the system reduced dust intensity by up to 50% in a controlled test environment. This indicates that the proposed model achieved its objective of reducing airborne dust concentrations by integrating digital technologies.

The TFT screen displayed real-time dust levels and water tank measurements, allowing for system status monitoring. The warning feature alerted users when water levels were low, ensuring operation reliability. Thus, the screen provided visual feedback on the performance of the system and served as an effective user interface.

While the system performed well in a small test box, its effectiveness was reduced when operating the prototype in a larger room due to spray distribution and coverage issues. This demonstrates the need for further design optimization of the spray module in order to increase the effectiveness of dust control in spacious areas.

VII. Conclusion

In conclusion, the Automatic Dust Reduction System achieved its primary goals by integrating sensors and actuators into an intelligent dust removal model. The prototype successfully reduced the dust concentration in a small area. Nevertheless, for large-scale dust control, spray coverage and distribution must be optimized. Overall, the project demonstrates the feasibility of combining innovative technologies to develop an IoT intervention for enhancing air quality. With the appropriate modifications and enhancements, the proposed dust removal system could be implemented on a larger scale to assist in mitigating the serious threats posed by dust pollution. Future work for the dust reduction system involves several key areas of improvement and expansion. Additionally, enhancing the efficiency of the spray module is crucial. This can be achieved by optimizing the nozzle designed spray pressure, adding more spray nozzles to ensure adequate dust suppression, and implementing an adaptive spraying system that adjusts spray patterns based on room size and dust levels.

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Q-KGSWS: Querying the Hybrid Framework of Knowledge Graph and Semantic Web Services for Service Discovery

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***Abstract*—In the era of big data, Knowledge Graphs (KGs) have become essential tools for managing interconnected datasets across various domains. This paper introduces a novel RDF (Resource Description Framework) based Knowledge Graph of Semantic Web Services (KGSWS), designed to enhance service discovery. Leveraging the versatile SPARQL query language, the framework facilitates precise querying operations on KGSWS, enabling customized service matching for user queries. Through comprehensive experimentation and analysis, notable improvements in accuracy (69.75% and 90.01%) and rapid response times (0.61s and 1.57s) across two semantic search levels are demonstrated, validating the efficacy of the approach. Furthermore, research questions regarding the interlinking of ontologies, methods for formulating automatic queries, and efficient retrieval of services are addressed, offering insights into future avenues for research. This work represents a significant advancement in the domain of semantic web services, with potential applications across various industries reliant on efficient service identification and integration. Future phases of research will focus on logical inference and the integration of machine learning-based graph embedding models, promising even greater strides in knowledge discovery within the KGSWS framework, thus reshaping the domain of semantic web services.**

Keywords—Ontologies; knowledge graph; semantic web services; SPARQL query language; OWLS; data integration; service discovery

I. Introduction

In today's rapidly changing computing environment, the fundamental paradigm of Service Oriented Architecture (SOA) is supported by core engineering principles of Reusability, Discoverability, and Interoperability. These principles provide a robust framework for orchestrating communication in distributed computing environments characterized by services encapsulated in discrete units. SOA leverages standardized interfaces and protocols, enabling seamless integration and communication between heterogeneous systems, thereby fostering a modular and extensible architecture [1]. Web Services (WS), the embodiment of SOA, play a pivotal role in contemporary enterprise solutions by enabling the integration of systems across organizational boundaries. WS, being self-described and disseminated by organizations, facilitate interoperable, machine-to-machine interactions and promote code reusability across networks. The orchestration of this integration relies on the convergence of components such as WSDL (Web Service Description Language), UDDI (Universal Description, Discovery and Integration), and SOAP (Simple Object Access Protocol), including the Service Consumer, Service Registry, and Service Provider. These components empower manual examination of WS within the UDDI repository, enabling users to identify services based on their specific functionalities [2] . However, the use of XML as the standard language for describing WS capabilities, while crucial for service description, introduces ambiguity in keyword-based matchmaking due to the absence of machine-understandable semantic information. This challenge in the software landscape necessitates the introduction of formal knowledge representation—a shared, universally harnessed resource within intricate software engineering systems [3] [4].

Semantic Web Services (SWS) build upon the foundation of WS by incorporating semantic extensions through metadata vocabularies from the Semantic Web. These extensions are either realized through semantic annotations known as SAWSDL (Semantic Annotations for WSDL) or by employing domain ontologies rooted in description logic, as seen in OWL-S. Ontologies, acting as metadata vocabularies, provide a formal, machine-understandable representation of concepts and their relationships within a domain, enhancing knowledge comprehension. Among the conceptual models defining SWS, OWL-S distinguishes itself through the integration of domain ontologies into WS descriptions. This integration enables logical reasoning, facilitating more precise and automated service discovery. Rules and constraints, defined on the concepts and properties of domain ontologies, serve as reference points for logical inference, fortifying specification, consistency, and conceptualization during service discovery. It, therefore empower domain experts to navigate knowledge contexts across domains with unambiguous precision. However, the intricacies of description logic formalism within domain ontologies, and the proliferation of SWS services have presented efficiency challenges for industries and organizations in terms of service discovery [5-7].

This paper confronts these challenges by leveraging the burgeoning paradigm of Knowledge Graphs (KGs). The unique capability of KGs to incorporate semantic metadata descriptions of entities makes them a prime candidate for complex querying through semantic web technologies, particularly SPARQL querying [8] [9]. This work introduces a pioneering approach: the creation of an RDF-based Knowledge Graph of Semantic Web Services (KGSWS) for service discovery, empowered by SPARQL-based question answering. At its core, this approach centers on generating interlinked data from domain ontologies to significantly augment service discovery accuracy. By employing advanced KG techniques and querying methodologies, SPARQL queries utilize the knowledge encapsulated in OWL-S service descriptions and their linked ontologies from KGSWS to address queries based on diverse user input/output requests. In essence, KGSWS uncover the hidden correlations between service descriptions and domain ontologies; and provide insightful recommendations to refine the user experience effectively and thereby serving as a bridge between the realm of SWS and KGs.

The paper's structure unfolds as follows: Section II delves into the Background elements and techniques underpinning this research. Section III explores related work, elucidating the context that motivated our research endeavor. Section IV frames the research questions to be in the proposed work. Section V meticulously details the proposed methodology, laying out the innovative approach that unifies SWS ontologies and KGs. Following this, Section VI unveils our experimental results, providing a comprehensive comparative analysis with related work. Finally, in Section VII, we conclude and outline future avenues for this research, illuminating the potential for further advancements in the domain of semantic web services.

II. Background

This section lays the groundwork for understanding the key components and concepts that underpin our research:

A. Semantic Web

Semantic Web is an advancement to the existing Web 2.0, designed to enable machines to process information intelligently, akin to human reasoning. This capability is achieved through the strategic use of semantic tags, imbuing data with what we call "Semantic Metadata." To exemplify, consider the concept of a "Service" in our context. Semantic Metadata goes beyond the term itself, distinguishing between a "Web Service" as a functional software component and a "Semantic Web Service" as a service enriched with semantic information, by providing specific details about its functionalities, inputs, and outputs, thereby facilitating precise and automated discovery. Structured Linked Open Data (LOD) is represented as a graph, interconnecting data across servers via Universal Resource Identifiers (URIs). RDF (Resource Description Framework) leverages URIs to denote relationships within this graph. In this structured environment, edges serve as the conduits for relationships between two resources, culminating in triplets within a directed graph. Ontologies, integral to the Semantic Web stack, enhance data within specific domains with semantic metadata. These ontologies furnish explicit, machine-understandable descriptions of concepts and their relationships, thus deepening data comprehension. OWL (Web Ontology Language), a logic-based language, forms the foundation of these ontology models, empowering RDF triple stores with rigorous constraints. The presence of OWL reasons ensures not only logical consistency but also real-time computation of inferred knowledge, thereby propelling data automation and interoperability. Incorporating Knowledge Graphs and the SPARQL Query language into the Semantic Web framework enhances our methodology for precise service discovery [10-13].

B. Knowledge Graph (KG)

Knowledge Graphs (KGs) are intricate representations of real-world entities as interconnected nodes, serving as central hubs for information retrieval and complex web searches. Their significance in encapsulating machine-understandable contextual information within heterogeneous environments has spurred intensive research in semantic matching. In 2012, Google pioneered the concept with its Google Knowledge Graph, featuring an impressive array of 570 million entities [14]. Subsequently, KGs such as Geonames, FactForge [15], Yago [16], Wikidata [17], and more have been carefully built, containing a lot of Linked Open Data (LOD). Across various domains, including retail, entertainment, healthcare, finance, and more, KGs have revolutionized question answering and knowledge discovery, underlining their versatility. KGs typically adopt either the subject-property-object (s,p,o) notation or the entity-relation-entity representation. Formally, a KG is defined as a subset of $(\mathcal{E} \times R \times \mathcal{E}) \cup (\mathcal{E} \times L_r \times L)$, where:

- $\mathcal{E}$ refers to the set of entities.
- R signifies the set of relations between entities.
- L_r signifies the set of relations linking entities with object of literals.
- L refers to the set of literals.

In semantic network modeling, triplets (s,p,o) denote metadata statements resulting from the mapping of subject (s) and object (o) to nodes or entities and their associated properties (p) to links or relations. In this structured framework, $\mathcal{E}$ must be a URI or a blank node representing the subject, while R and Lr must be URIs, and the object entity can be a URI, blank node, or literal. In the context of SWS discovery, KGs herald a transformative shift from big data discovery to intelligent data discovery. Knowledge integration from domain ontologies plays a pivotal role in this transformation [18].

C. SPARQL Query

SPARQL Protocol and RDF Query Language (SPARQL) stands as the preeminent query language for Semantic Web data, providing a means to interrogate extensive RDF-based KGs. Unlike SQL, tailored for relational databases, SPARQL caters to NoSQL graph databases like KGs, enabling the integration of knowledge from diverse sources to derive new insights. Built on the HTTP transport layer protocol, SPARQL facilitates querying information from multiple KGs via federated queries. It employs graph pattern matching, represented as subject, predicate, and object (s,p,o) triple patterns, to uncover solutions. SPARQL supports four query types: ASK, SELECT, CONSTRUCT, and DESCRIBE, each designed for specific querying purposes [19]. By harnessing the capabilities of SPARQL, our methodology transcends conventional querying techniques, providing a sophisticated means to navigate and utilize the rich semantic information encapsulated within the KG.

III. Related Work and Motivation

Over the past decade, substantial research efforts have been dedicated to enhancing the efficiency of Semantic Web Services (SWS) discovery algorithms. These algorithms aim to facilitate the discovery, selection, composition, classification, and ranking of SWS based on various functional and non-functional parameters. Numerous matchmaking algorithms have been devised, leveraging both logical and non-logical functional parameters of SWS. These algorithms enhance the selection and recommendation process for SWS. Initial variant of OWLS-M0 [20] used only logic based semantic similarity measure on I/O for service discovery. However, the other variants in [20] and notable work by [21, 22] employed hybrid matchmakers that consider logical and non-logical parameters from OWL-S and WSMO services. Semantic similarity metrics such as cosine similarity, loss-of-information, and Jensen-Shannon divergence were employed to assess the compatibility of services. One challenge encountered in this context is the time-consuming creation of matchmaker ontologies, particularly when handling a substantial number of services. To address this, [23, 24] introduced a caching-based mechanism called Service Discovery Caching (SDC). SDC involves the construction of a graph to cache frequently used services, thereby mitigating the time overhead. Another line of research [25] employed First Order Logic (FOL) to formally describe service capabilities. The study utilized SPARQL 1.0 for querying services based on their descriptions, particularly in cases where services provided Preconditions and Effects (PE) descriptions. Although promising, this method was constrained by the limited availability of services with PE descriptions in the dataset, limiting its generality. Efforts to reduce the problem space of service searching led to prefiltering mechanisms [26-28]. These mechanisms were designed to enhance existing matchmaker engines using SPARQL queries, significantly improving response times. Nevertheless, the challenge of semantic matching persisted, particularly for complex concepts and relations within domain ontologies. Working on the same OWL-S dataset, the work in [29] have used unsupervised learning methods like DBSCAN clustering to cluster the services semantically closed and thereby finding the semantically closed cluster to user requirement using Latent Semantic Analysis (LSA). An ensemble model based approach in [30] use decision tree and logistic regression for service classification and recommendation of top-10 services. However, none of these works implemented the concept of KGs in the domain of SWS. The work cited in study [31] [32] employed machine learning methodologies; specifically K-Means clustering was used in [31] to generate a Service Ontology from SWS corpus. Results demonstrated that the generated ontology can be used for the discovery mechanism. Later work in [32] utilized first K-Means clustering and then K-Nearest Neighbors (KNN) for classification. This analysis yielded a noteworthy accuracy rate of 89.28%. However, it's essential to emphasize that this algorithm was rigorously tested within a restricted range of domains. Another work in [33] used part of OWL-S dataset i.e. 30000 triplets to add domain knowledge in KG and also for training and testing purpose of user’s intent. However, with advanced machine learning methods, the overall accuracy of SWS discovery has improved. However, most of these works [29-32] focused on a subset of domains within the OWLS collection, and none of the works have implemented an automatic querying method for user queries. Instead of using the relevance file provided for OWLS-TC as per user queries, different methods have been employed to compute evaluation metrics.

In parallel with advancements in SWS discovery, Knowledge Graphs (KGs) have emerged as a powerful tool for representing and retrieving knowledge from large interlinked datasets. These KGs integrate domain ontologies at a universal level, creating extensive graphical representations of interlinked data that support complex queries and unified knowledge discovery. Recent work on KGs has generated KGs in different domains whereas some works perform querying over the existing KGs to improve the tasks like recommendation systems, link prediction, node classification, and knowledge discovery [34-36]. Another line of works in [37-40] generate SPARQL queries from natural language for existing KGs like DBpedia, Wikidata for complex querying. Furthermore, Graph Neural Network-based learning models have been employed to enhance KGs' performance in tasks such as link prediction and multihop querying [41-43]. Our motivation for this research stems from the intersection of SWS discovery and KGs. Both domains utilize ontologies as a foundation, making them amenable to integration. While previous works have primarily focused on matchmaking within SWS or querying KGs independently, there is a notable gap in seamlessly integrating SWS discovery with Knowledge Graphs (KGs) specific to our domain of SWS for service discovery. This is the key motivation behind our research. We aim to bridge these domains by creating a Knowledge Graph of Semantic Web Services (KGSWS). This integrated approach enables enhanced SWS discovery using KG-based querying techniques.

IV. Research Questions

The motivation for this proposed work arose from an extensive review of related research papers and the challenges discussed in the field. Our objective is to establish a centralized Knowledge Graph (KG) for Semantic Web Services (SWS) and address the following research questions:

1) How can ontologies from different domains be interlinked to form an extensive Knowledge Graph enriched with semantic metadata thereby enhancing the discovery of SWS?

2) What methods can be used to formulate the automatic queries on the KG, aligned with varying numbers of inputs-outputs for effective querying purposes?

3) How can we efficiently retrieve SWS from big KG that precisely matched the user requirements for service discovery? Additionally, how can we identify the closely related services when an exact match is not available, maintaining the integrity of the user's query?

V. Proposed Approach

In this section, the detailed experimentation done to design a framework for discovery of relevant services across KGSWS has been discussed. The framework includes the steps required to create, visualize, and query the KGSWS as shown in Fig. 1. The detailed insights to these steps have been discussed in Phase 1 and Phase 2 of the framework. Phase 3 discussed the validation process of the results.

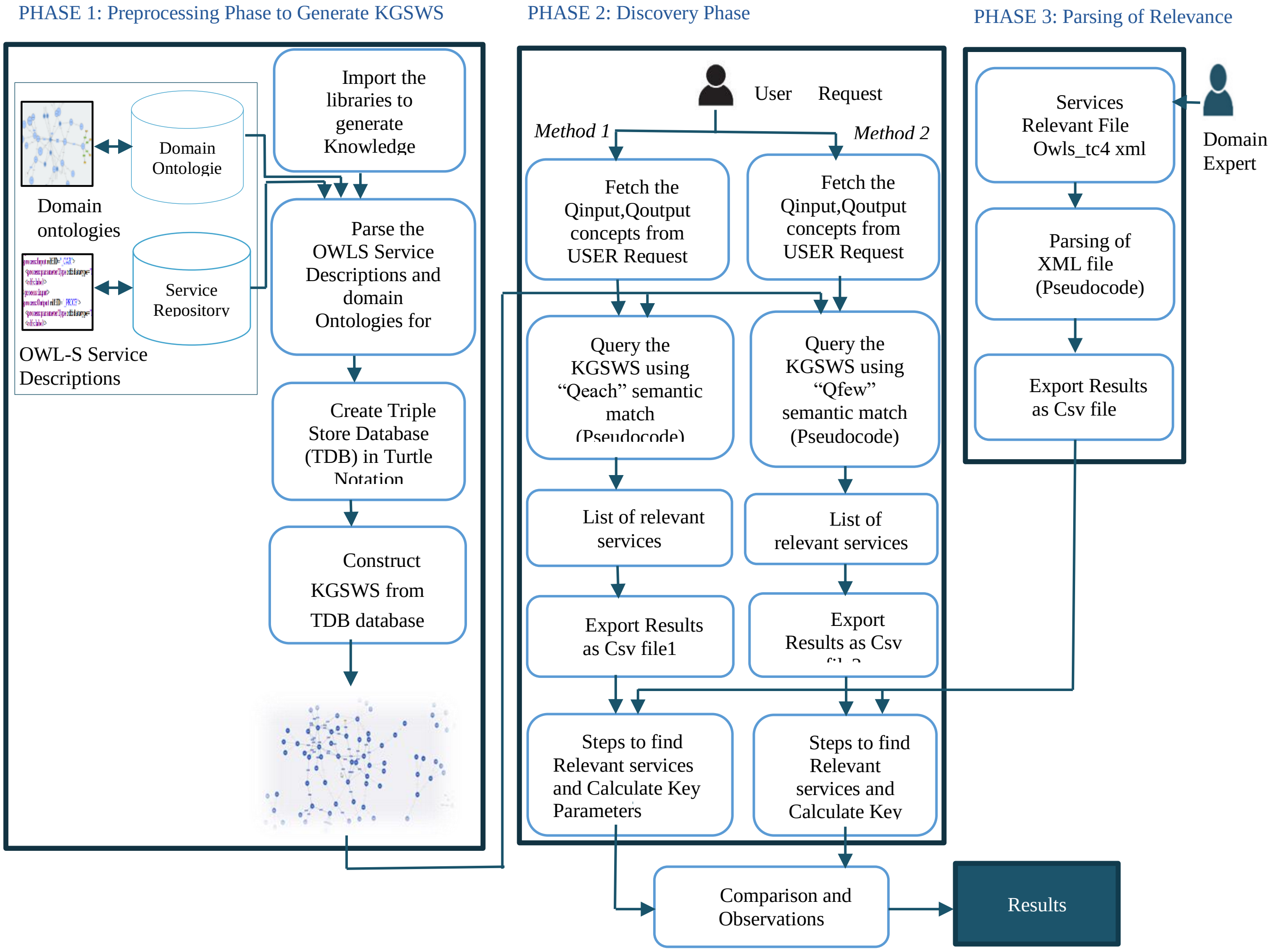

PHASE 1: Preprocessing Phase to Generate KGSWS
PHASE 2: Discovery Phase
PHASE 3: Parsing of Relevance
Domain Ontologie
Domain ontologies
Service Repository
OWL-S Service Descriptions
Import the libraries to generate Knowledge
Parse the OWLS Service Descriptions and domain Ontologies for
Create Triple Store Database (TDB) in Turtle Notation
Construct KGSWS from TDB database
User Request
Method 1
Method 2
Fetch the Qinput,Qoutput concepts from USER Request
Fetch the Qinput,Qoutput concepts from USER Request
Query the KGSWS using "Qeach" semantic match (Pseudocode)
Query the KGSWS using "Qfew" semantic match (Pseudocode)
List of relevant services
List of relevant services
Export Results as Csv file1
Export Results as Csv fil 2
Steps to find Relevant services and Calculate Key Parameters
Steps to find Relevant services and Calculate Key
Services Relevant File Owls_tc4 xml
Domain Expert
Parsing of XML file (Pseudocode)
Export Results as Csv file
Comparison and Observations
Results

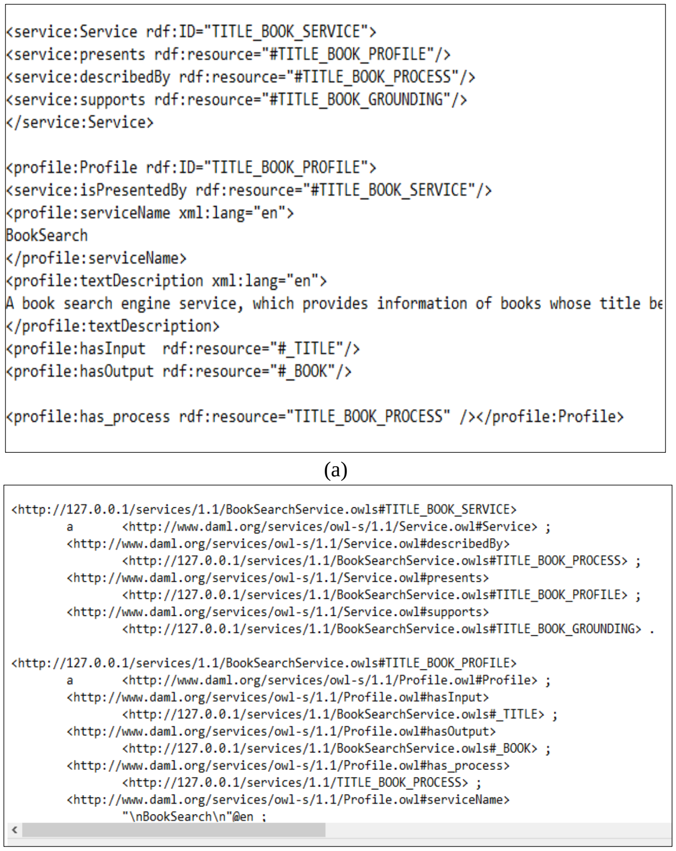
Fig. 1. Proposed work methodology.

A. *Phase 1: Preprocessing Phase to Generate Knowledge Graph*

The core step of our approach is the creation of a Knowledge Graph designed explicitly for Semantic Web Services (KGSWS). This phase describes the steps involved in constructing the KGSWS from the OWL-S service descriptions and their associated domain ontologies with an example. Through this, semantic metadata was integrated with KGSWS that forms the backbone of the proposed approach.

1) OWL-S service descriptions and KGSWS Construction: OWL-S services are based on frameworks that add semantic extensions to non-semantic web services using domain ontologies. In OWLS approach, Service Profile describes the capabilities of the service and refer as the upper ontology, Service Modelling demonstrates data flow and control flow within the services and Service Grounding specify the procedure of interaction with these services using protocols and message formats. OWL-S service description is mainly provided by the upper ontology Service Profile where different terms describe the inputs, outputs, preconditions, and their effects (IOPE); postconditions, assumptions based on the transition rules, if required. Once the service based on the brief description of IOPE concepts in the Profile is selected; Process Model related with Service Profile is used for further interaction with these services by linking them to their domain ontologies. For instance, consider the Profile and Process Model in the Service Description of finding author of the book as shown in Fig. 2(a). In the Profile of the service <profile:serviceName>, <profile:textDescription>, <profile:hasInput> and <profile:hasOutput> provides the information of the book whereas the <process:

parameterType> in the process model linked the I/O concepts “Book” and “Author” to the ontology “books.owl” for the semantic matching of the concepts. In order to construct KGSWS from of these services, these I/O terms are referred as entities and their associated properties and restrictions form the relations are then mapped to literal or another entity. Since these I/O concepts refer to some domain ontologies description in the Process Model, these ontologies are also linked in KGSWS by extracting an interoperable definition of each concept from their properties and restrictions from domain ontology. This was done by first serializing the service descriptions concepts and their associated ontologies to Triple Notation (Turtle Notation. ttl). Apache Jena Fuseki was used for integration, thus all the OWL mappings, alignment axioms that indicate equivalence or relationships between terms were preserved. Afterwards, KGSWS graph was created using network and rdf based libraries like rdflib, networkx in Python which consists of 1,21,542 Triplets. Fig. 2(b) shows the snippet of turtle representation for example shown in Fig. 2(a).



```
<service:Service rdf:ID="TITLE_BOOK_SERVICE">
<service:presents rdf:resource="#TITLE_BOOK_PROFILE"/>
<service:describedBy rdf:resource="#TITLE_BOOK_PROCESS"/>
<service:supports rdf:resource="#TITLE_BOOK_GROUNDING"/>
</service:Service>

<profile:Profile rdf:ID="TITLE_BOOK_PROFILE">
<service:isPresentedBy rdf:resource="#TITLE_BOOK_SERVICE"/>
<profile:serviceName xml:lang="en">
BookSearch
</profile:serviceName>
<profile:textDescription xml:lang="en">
A book search engine service, which provides information of books whose title be
</profile:textDescription>
<profile:hasInput  rdf:resource="#_TITLE"/>
<profile:hasOutput rdf:resource="#_BOOK"/>

<profile:has_process rdf:resource="TITLE_BOOK_PROCESS" /></profile:Profile>
```

(a)

```
<http://127.0.0.1/services/1.1/BookSearchService.owls#TITLE_BOOK_SERVICE>
        a       <http://www.daml.org/services/owl-s/1.1/Service.owl#Service> ;
        <http://www.daml.org/services/owl-s/1.1/Service.owl#describedBy>
                <http://127.0.0.1/services/1.1/BookSearchService.owls#TITLE_BOOK_PROCESS> ;
        <http://www.daml.org/services/owl-s/1.1/Service.owl#presents>
                <http://127.0.0.1/services/1.1/BookSearchService.owls#TITLE_BOOK_PROFILE> ;
        <http://www.daml.org/services/owl-s/1.1/Service.owl#supports>
                <http://127.0.0.1/services/1.1/BookSearchService.owls#TITLE_BOOK_GROUNDING> .

<http://127.0.0.1/services/1.1/BookSearchService.owls#TITLE_BOOK_PROFILE>
        a       <http://www.daml.org/services/owl-s/1.1/Profile.owl#Profile> ;
        <http://www.daml.org/services/owl-s/1.1/Profile.owl#hasInput>
                <http://127.0.0.1/services/1.1/BookSearchService.owls#_TITLE> ;
        <http://www.daml.org/services/owl-s/1.1/Profile.owl#hasOutput>
                <http://127.0.0.1/services/1.1/BookSearchService.owls#_BOOK> ;
        <http://www.daml.org/services/owl-s/1.1/Profile.owl#has_process>
                <http://127.0.0.1/services/1.1/TITLE_BOOK_PROCESS> ;
        <http://www.daml.org/services/owl-s/1.1/Profile.owl#serviceName>
                "\nBookSearch\n"@en ;
```

(b)

Fig. 2. (a) Example of service description structure [42]. (b) Shows the snippet of turtle notation for above service description example used to construct KGSWS.

B. *Phase 2: Discovery Phase*

The main objective of this phase was to perform queries over KGSWS created in phase 1 of the proposed framework.

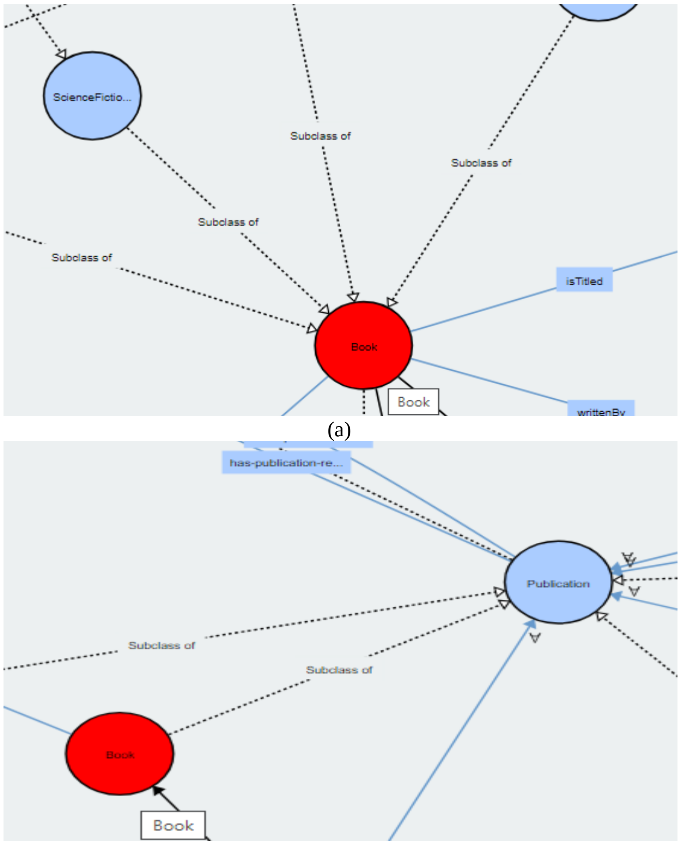
1) Querying and Searching from KGSWS: KGSWS, generated in Phase 1, comprises millions of entities and their attributes represented as nodes and edges. To query such specialized KGs, specialized knowledge of the querying language and a deep understanding of the underlying structure are required. Addressing the challenge of searching for relevant services based on the I/O concepts mentioned in the user request, we automated the generation of SPARQL queries based on the OWL-S service description model. These queries are then executed across the KGSWS to search and retrieve relevant services. The proposal used SPARQL 1.1 query due to its efficient results in pre filtering of domain wise services [28] and recommendation by W3C for querying over graphical databases. However, the work lacked its own matchmaker and has not integrated different domain ontologies to create big KG due to which services based on equivalent concepts were not retrieved. For instance, to find the name of books giving title or other information as input retrieve the service no.1 and 2 with output concept “Book” from “books.owl” domain ontology as valid services as shown in Table I. In the given query, the service no. 3 having interface description “Publication-number” as input and “Book” as output concept from “univ.owl” is also valid due to equivalence relation of “books:Book ≡ univ:Book” where books and univ are namespaces for “books.owl” and “univ.owl” ontologies respectively.

As show in Fig. 3(a) of “books.owl” ontology, the “Book” concept was used to describe information of different types of books and in Fig. 3(b) of “univ.owl”, the same highlighted concept was added as a subclass of “Publication” concept. To query the KGSWS, two methods were implemented with a view to include different degree of semantic matching.

2) Semantic matching: To evaluate the performance of different degree of semantic match of concepts during discovery of services from their knowledge graph, two methods namely Method 1 and Method 2 were used to generate query wise relevant list. These two matchmaking algorithms focus solely on the input and output parameters of the service and employ two levels of semantic concept matching, namely ‘Q_{each}’ and ‘Q_{few}’ as outlined in Table II. This is followed by the pseudocodes for both discovery methods. The Phase 1 of constructing KGSWS is followed by the process of parsing I/O concepts based on user requests. Subsequently, a SPARQL query, guided by steps 9-12, was executed to retrieve a list of relevant services using Select, Where, Filter, Bind, Regular expressions options in the query. For the determination of services using "Q_{each}," each concept in the user request was considered, and services aligned with equivalent concepts in other ontologies within the same domain were retrieved through the 'owl:equivalentClass' restriction. Additionally, for "Q_{few}," beyond the steps involved in "Q_{each}," a 'UNION' operation in the SPARQL query was introduced to filter out entirely irrelevant services.

TABLE I. SOME RELEVANT SERVICES TO FIND THE BOOK NAME FROM ITS GIVEN INFORMATION

S.No.	WSName	Textual Description of the Functionality	Interface Description	
			Input	Output
1.	BookFinder.owls	The services retrieves the book information having title as input	books:Title	books:Book
2.	BookSearchService.owls	Search engine for book	books:Title	books:Book
3.	Publication_book_service.owls	The service retrieve the book name with given publication number	niv:Publication	univ:Book



(a)

(b)

Fig. 3. (a) Books.owl. (b) Univ.owl.

TABLE II. DEMONSTRATED THE METHODS FORMULATION IN DESCRIPTION LOGIC

Method No.	Method Name	Description Logic Representation	Description
Method 1	Q_{each}	If $I_{concept}(S) \equiv I_{concept}(R_q)$ ^ $O_{concept}(S) \equiv O_{concept}(R_q)$	Service S concepts are semantically equivalent to R_q Concepts
Method 2	Q_{few}	If $I_{concept}$ $(R_q) \subseteq I_{concept}$ (S) ^ $O_{concept}(R_q) \subseteq O_{concept}(S)$	R_q concepts matched to some concepts of service S
where $I_{concept}(S)$, $I_{concept}(R_q)$, $O_{concept}(S)$, and $O_{concept}(R_q)$ represents the inputs/outputs concepts of advertised and request services respectively			

Pseudocode for Method 1: Q_{each}

```
Input:
Given user query refer to required $Q_{input}$ and $Q_{ouput}$ where:
        $Q_{input}$: List of required input concepts in the query
        $Q_{ouput}$: List of required output concepts in the query
Output:
                RSL: Relevant Service List
Local Resources:
KGWS = Knowledge Graph of Services
and their Ontologies
For each query, Parse $Q_{input}$ and $Q_{output}$
Parse the TDB knowledge graph of services
Check if the predicate of the triplet is service:Service
For each service, retrieve the process Input and Output tags
from the triplet
Retrieve <process:parameterType> tags of process Input
and Output to retrieve domain ontology
Apply filters for semantic matching of "each" concept of
$Q_{input}$ and $Q_{ouput}$.
Generate RSL($Q_{input}$, $Q_{ouput}$, RSL- Relevant Service List)
Repeat
```

Pseudocode for Method 2: Q_{few}

```
Input:
Given user query refer to required $Q_{input}$ and $Q_{ouput}$ where:
        $Q_{input}$: List of required input concepts in the query
        $Q_{ouput}$: List of required output concepts in the query
Output:
                RSL: Relevant Service List
Local Resources:
KGWS = Knowledge Graph of Services
and their Ontologies
For each query, Parse $Q_{input}$ and $Q_{output}$
Parse the TDB knowledge graph of services
Check if the predicate of the triplet is service:Service
For each service, retrieve the process Input and Output tags
from the triplet
Retrieve <process:parameterType> tags of process Input
and Output to retrieve domain ontology
Apply filters for semantic matching of "few" concepts of
$Q_{input}$ and $Q_{ouput}$.
Generate RSL($Q_{input}$, $Q_{ouput}$, RSL- Relevant Service List)
Repeat
```

C. Phase 3: Parsing of Relevance File

In this phase, the list of services generated in Phase 2 was validated against the services in the relevance file provided by domain experts for "OWL-TC4."

The file features a <binaryrelevanceset> root tag containing <request>, <name>, and <uri> tags for each service request, as shown in the above structure of XML relevance file. These tags were employed to assign a unique ID to each request, with service request names based on the requested service's functionality. The <uri> tag contains a unique address to identify the request on the web. Furthermore, each <request> has a <ratings> tag containing multiple <offer> tags specifying the <name>, <uri>, and binary relevance in the <relevant> tag of the service. These requests have been parsed and the relevant information was stored in a CSV relevance file using Python libraries for hierarchical structures as shown in pseudocode. The service list from Phase 2 was compared with this relevance file to determine the key parameters of the model, as discussed in the next section.

Pseudocode: To Parse XML DOM

```
1. Import the XML libraries and other hierarchical libraries
2. Parse the relevance file 'owls-tc4.xml'
3. Get the root of the structure
   //To match the name and uri of each query request given by the user
4. For each user request as child in xml file
5. Retrieve the name and uri of the request
   //Find the name, uri, and relevance value of services for particular request
6. For each item offer giving the details of the service
7. Retrieve the service name, uri and its relevance value.
8. Append the results in data frame //As hierarchical structure
9. Export the results as "outputxml.csv"
```

Structure of the XML Relevance File

```
<binaryrelevanceset> //for the binary relevance sets
<request ...>
<name ... />
<uri .../>
<ratings>
<offer ...> //each request contains multiple offers
<name ... />
<uri .../>
<relevant>value</relevant>
//here the value can be either 0 or 1
</offer>
...
</ratings>
</request>
...
</binaryrelevanceset>
```

VI. Results and Discussion

In this section, a comprehensive analysis of the performed experiments has been discussed to assess the performance and efficiency of our proposed framework. The section commenced by describing the experimental scenario and the dataset used for testing. Following this, an in-depth analysis of the results has been done to emphasize significant observations and comparisons between our approach and baseline methods.

A. *Experimental Scenario*

In order to test the performance of our proposal, ontology based SWS test collection OWLS-TC v4 [44] was used to create KGSWS. As shown in Table III, the collection contains 1083 services from nine domains namely Education, Medical Care, Food, Travel, Communication, Economy, Weapon, Geography, and Simulation. These services were based on 48 domain ontologies. KGSWS consists of 1,21,542 triplets generated from the integration of these 1083 service descriptions and their corresponding 48 domain ontologies. Further, 38 test queries with varying number of input output concepts based on the domains were executed against KGSWS using two different SPARQL query methods.

TABLE III. Domain Names and Number of Services in each Domain

S.No.	*Domain*	*No. of Services*
1	*Education*	279
2	*Medical Care*	73
3	*Food*	34
4	*Travel*	197
5	*Communication*	59
6	*Economy*	325
7	*Weapon*	40
8	*Geography*	60
9	*Simulation*	16
	Total	*1083*

B. *Analysis of Results*

In this subsection, we provide a comparative analysis of our proposed methods i.e. Method 1 (Q_{each}) and Method 2 (Q_{few}), against baseline approaches. The key parameters that were used to compare the performance of these methods are given below in Table IV [45]. The Macro-Averaged Precision Recall metrics was used to give equal relevance to each test query and its value lies in the range [0, 1]. The relevance file provided for OWLS-TC (as discussed in Phase 3) was utilized to compute the key parameters of the methods in the proposed framework.

1) Analysis of method 1 results: As discussed, Method 1 employed each concept matching approach, aligning service requests with the concepts within the KGSWS. This precision-oriented method demonstrated noteworthy results as shown in Fig. 4(a) and Fig. 4(b). It retrieved fewer or zero irrelevant services, leading to significantly higher precision in most cases. Also, Method 1 exhibited an average query response time of a mere 0.61 seconds, showcasing its efficiency. However, this method faced challenges in test cases 8, 17 and 22, where it failed to locate any relevant service matching each concept, leading to a precision value of zero and due to equal importance of each query it dropped the overall precision value even if in most of the cases the values reaches 1 as shown in Fig. 4(a). Furthermore, the proposed model did not include logical inferred "subclass" concepts during the matchmaking of each concept. Due to this, all the relevant services having input-output concepts as direct subclass concepts of requested concepts in the query were not retrieved dropping the macro-averaged recall value to 49.14%. But, the overall accuracy of the model is 69.75% better than one of the existing work [20].

TABLE IV. KEY PARAMETERS USED FOR THE PERFORMANCE EVALUATION OF THE MODEL

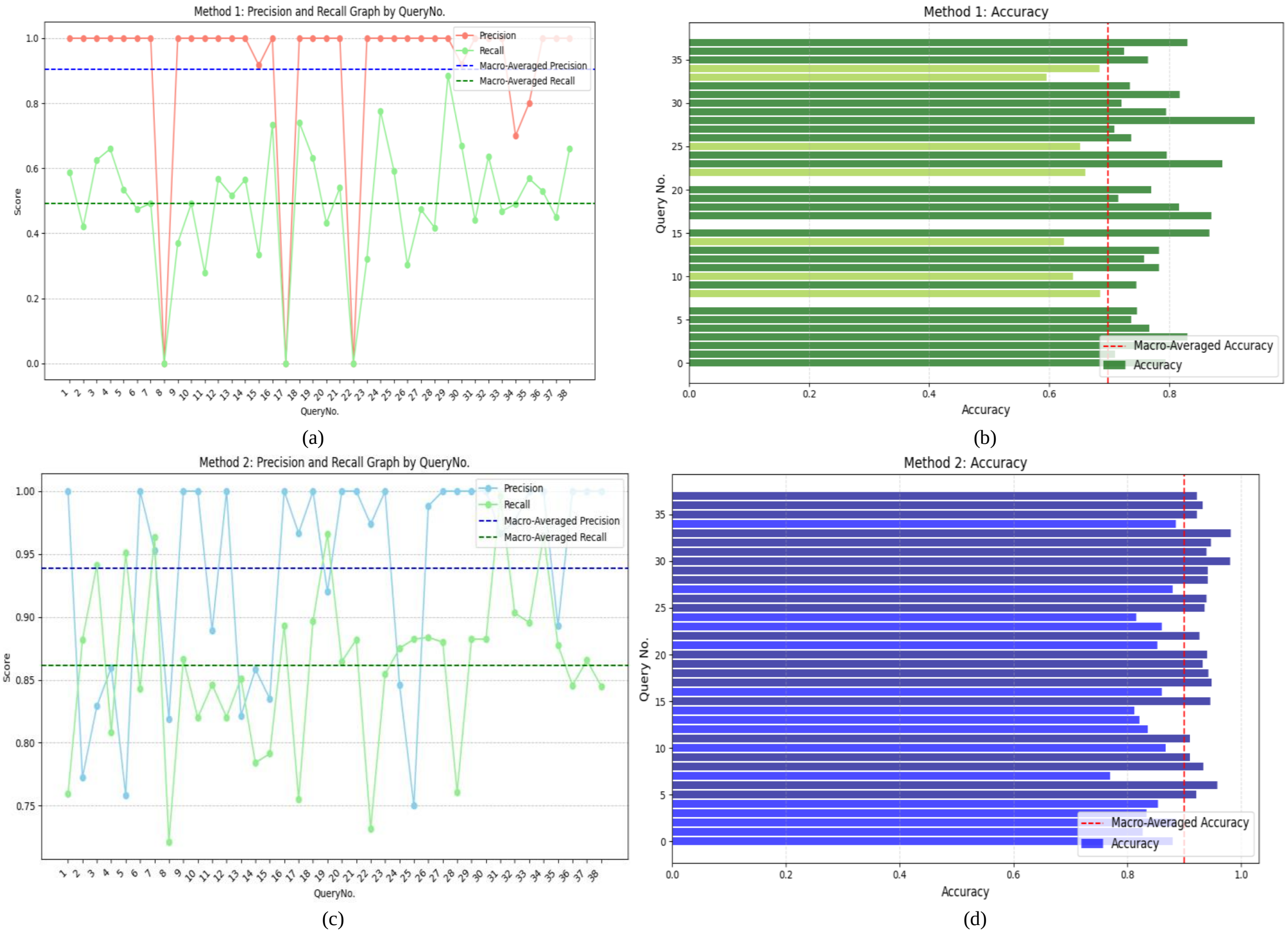
Precision	Precision in case of SWS is defined as the number of relevant services out of the total number of services retrieved by the framework. Mathematical equation to calculate the Precision value is given as follows: $\frac{S_{relevant}}{S_{relevant} + S_{irrelevant}}$ where, $S_{relevant}$ gives the number of relevant services retrieved, and $S_{irrelevant}$ gives the number of irrelevant services retrieved
Recall	Recall is computed by taking the fraction of relevant services retrieved out of the total relevant services given in the relevance file by domain expert. Mathematical equation to calculate the Recall value is given as follows: $\frac{S_{relevant}}{S_{relevant} + S_{relevantNR}}$ where, $S_{relevant}$ gives the number of relevant services retrieved, and $S_{relevantNR}$ gives the number of relevant services not retrieved by the framework
Macro-Average Precision	Macro Average Precision is used to compute the arithmetic mean of the precision of each test query in case of multiclass classification. $\sum_{q=1}^{N} \frac{Precision}{N}$ where, q represents the number of test queries and $Precision_q$ gives the precision value of q^{th} query
Macro-Average Recall	Macro-Average Recall is used for multiclass classification and is computed by taking arithmetic mean of each test query recall value. $\sum_{q=1}^{N} \frac{Recall_q}{N}$ where, q represents the test query and takes values up to N, and $Recall_q$ gives the recall value of q^{th} query
Accuracy	Accuracy provides the overall performance of the model by computing the ratio of correct predictions out of total predictions done by the model.
Average Query Response Time	Average Query Response Time (Avg. Q_{rt}) is computed by taking the average of total response time taken to execute all the test queries.

- Logical Inferencing over KGSWS

The incorporation and interconnection of ontologies within KGSWS not only enhance the outcomes, as discussed in the previous section, but also pave the way for easier reasoning, composition, and classification in the future. Reasoning over KGSWS involves incorporating logically inferred concepts through the "subclass" symmetric relation. For example, when searching for services that provide the price of a given book, services that yield "MaxPrice" or "RecommendedPrice" as output, with "book" as input, are also deemed relevant. This relevance stems from their subclass relationship with the "Price" concept. However, the proposal did not account for the addition of logically inferred subclass concepts from the given concepts, leading to a decrease in the overall accuracy of Method 1.

2) Analysis of Method 2 results: Method 2, characterized by looser restrictions on the semantic match of I/O concepts, yielded contrasting results as shown in Fig 4(c) and Fig 4(d). This enhancement allowed the automatic retrieval of services sharing subclass relationships with some concepts of user concepts thereby capturing more closely related services. This flexibility leads to improved recall values, as Method 2 can identify a broader range of relevant services. This method proved beneficial in the worst cases of Method 1, where it retrieved some relevant services and achieved non-zero precision. However, this came at the trade-off of retrieving some irrelevant services, resulting in a decrease in average precision. This highlights the potential of Method 2 for more comprehensive service discovery, albeit at the expense of precision. Table V demonstrates the macro-averaged results, accuracy and average Q_{rt} of the two methods.

3) Comparison with existing frameworks: Comparing our experimental results with some published results of other existing works on the same dataset (see Table VI), it was observed that our proposed method demonstrated superior performance in terms of average response time and accuracy. Notably, the two-step approach in [28] involving prefiltration and subsequent matchmaking incurred a higher average query response time compared to our approach. This is a significant achievement, considering that our search was conducted over the integrated KGSWS, underlining the efficiency and swiftness of our approach. Moreover, the matchmakers of [20] exhibited longer response times, primarily attributable to the addition of concepts to a new matchmaker ontology for each request. In contrast, our approach, which seamlessly integrates the advantages of in depth querying over Knowledge Graph, overcame this bottleneck, leading to a more streamlined and efficient service discovery process. An important observation in our results was that while some subsequent studies [29-32] explored machine learning-based classification techniques, none had harnessed the potential of the Knowledge Graph within this domain.



(a)

(b)

(c)

(d)

Fig. 4. (a) Macro-averaged precision recall of method 1. (b) Query wise accuracy of method 1 and the dotted redline shows the macro-averaged accuracy of the model. (c) Macro-averaged precision recall of method 2. (d) Query wise accuracy of method 2 and the dotted redline shows the macro-averaged accuracy of the model.

TABLE V. KEY PARAMETERS RESULTS GIVEN BY TWO METHODS "Q_{EACH}" AND "Q_{FEW}"

Key Parameters	Method 1	Method 2
Macro-Averaged Precision	0.9036	0.9388
Macro-Averaged Recall	0.4914	0.8614
Accuracy	0.6975	0.9001
Average Query Response Time (in s)	0.61 s	1.57s

C. Discussion

The proposed work, used the advanced potential of KGs for semantic enrichment and querying, overcomes the limitations of previous approaches by introducing an integrated composite schema known as KGSWS for querying. This schema allows Method 1 and Method 2 to incorporate more relevant services within the same domain using different levels of filtering and regular expressions during the discovery process. The integration of domain ontologies and service descriptions in KGSWS enables the alignment of heterogeneous concepts within the same domain with user-requested concepts, thereby increasing the accuracy of both Method 1 and Method 2. However, as the work does not include logical reasoning over KGSWS, the performance metrics of Method 1 experienced a decline to 69.75% due to the matching of each concept of the user-requested query. Additionally, while Method 2 benefits from the inclusion of more equivalent concepts within the same domain, allowing for the automatic inclusion of more relevant services with loose concept matching using filters and regular expressions, this also entails the inadvertent inclusion of some irrelevant services. Compared to previous approaches, our proposed framework offers a comprehensive querying solution rather than relying on pre-filtering through querying on exiting matchmakers [28], which can lead to increased response times. Furthermore, unlike existing methods [20] that create matchmaking ontologies for discovery, our approach does not require such intermediary steps. For validation purposes, our work utilized the relevance file provided for the OWLS dataset in Phase 3 instead of employing alternative methods [29-33] to find relevant services, thereby enhancing the reliability of the framework. Additionally, we considered the complete OWLS-TC dataset rather than using its subset to generate KGSWS and further for service discovery. The framework also allows for the automatic generation of queries based on user-requested concepts, offering a generic and streamlined approach to querying.

TABLE VI. COMPARISON OF ACCURACY AND QUERY RESPONSE TIME OF EXISTING FRAMEWORKS WITH THE PROPOSED FRAMEWORK

	Accuracy (%)	Average Q_{rt} (in sec.)
Method 1	69.75	0.61 s
Method 2	**90.01**	**1.57s**
OWLS-M0 [20]	49.55	57.33s
OWLS-MX3 (M3) [20]	82.96	58.46s
SPARQLent [28]	72.02	55.00s
HELSWSR [30]	85.60	-
-[29]	83.09	-
- [32]	89.28	-

VII. CONCLUSION AND FUTURE SCOPE

In this paper, we have presented a framework for the automatic discovery of SWS through the use of SPARQL querying over KG. By introducing the KGSWS framework, a paradigm shift has been made by offering more precise and machine understandable context during automatic matchmaking of services. The integration of domain ontologies in KGSWS introduces a new level of semantic richness that effectively resolved the ambiguity associated with keyword-based matchmaking of WS. In conclusion, our work contributes to the field of SWS discovery by efficiently retrieving the relevant services aligned with the concepts in user request. Our approach also addresses several research questions discussed at the outset of this work.

A. Addressing Research Questions

1) How can ontologies from different domains be interlinked to form an extensive Knowledge Graph enriched with semantic metadata thereby enhancing the discovery of SWS?

Our framework successfully accomplished this by constructing the KGSWS from OWL-S service descriptions and their associated domain ontologies that forms a centralized repository of semantic metadata to enhance the discovery process of services.

2) What methods can be used to formulate the automatic queries on the KG, aligned with varying numbers of inputs-outputs for effective querying purposes?

Our experiments demonstrated the effectiveness of our approach in generating and executing general-purpose queries over KGSWS. The capabilities of two semantic matching methods namely "Q_{each}" and "Q_{few}," have been evaluated in answering user queries based on varying input/output parameters.

3) How can we efficiently retrieve SWS from big KG that precisely matched the user requirements for service discovery? Additionally, how can we identify the closely related services when an exact match is not available, maintaining the integrity of the user's query?

The semantic matching methods provide a practical solution to this challenge. The "Q_{each}" method excels in retrieving precisely matched services whereas the "Q_{few}" method retrieved closely related services when exactly matched services are not available.

B. Future Scope

While our proposed work has achieved promising results, several avenues for improvements and future research exist:

1) Logical inference: In future work, the inclusion of logical inferencing techniques in Q_{each} semantic matching can enhance the macro-averaged recall and thereby accuracy of our framework.

2) Scalability and machine learning based models: As the number of SWS and their associated ontologies continues to grow, scalability remains a critical concern. The incorporation of machine learning based graph embedding models can efficiently handle large KGs and also enable more accurate service recommendations.

VIII. DECLARATIONS

Author contribution P.T and L.S conceived the idea. P.T executed the experiments and wrote the article. L.S did edition and corrections.

Data Availability Not applicable

Code Availability Not applicable

Conflict of Interest the authors declare no competing interests

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Rural Revitalization Evaluation using a Hybrid Method of BP Neural Network and Genetic Algorithm Based on Deep Learning Model

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***Abstract*—The rural revitalization strategy is a comprehensive plan for supporting rural revival in the new development stage while prioritizing agricultural and rural area development. Establishing a rural revitalization evaluation model will help monitor and guide the development of rural revitalization strategies and comprehensively deepen rural reforms. This research combines the benefits of the BP neural network with the genetic algorithm, introduces the genetic algorithm in optimizing the weights and thresholds of the BP neural network, and develops a GA-BP neural network model to evaluate and predict rural rejuvenation. The research findings demonstrated that the GA-BP neural network model possesses rapid convergence, accuracy, and stability in assessing and predicting rural revival and can evaluate and predict rural revitalization well.**

Keywords*—The rural revitalization strategy; deep learning model; the GA-BP neural network; evaluation model

I. Introduction

The rural revitalization strategy marks that China has entered a new era in solving the “three rural” issues [1]. It will be significant for governments at all levels to understand the implementation process of rural revitalization, implement targeted policies, and give full play to the ingenuity, enthusiasm, and creativity of the country’s cadres and the masses [2].

The evaluation of rural revitalization might establish objectives and requirements. The general conditions for rural rejuvenation were described as “prosperous industries, livable ecology, civilized rural customs, effective government, and rich life” [3]. To make the general demands of the rural revitalization strategy and the “three-step” objective concrete and executable, an evaluation system for rural revitalization must be developed. Rural revitalization evaluation is conducive to an intuitive description of the overview of rural revitalization and construction, drawing a blueprint for the future vision of rural revitalization so that decision-makers, commanders, and builders of rural revitalization have a clear direction and goal of efforts and have a clear vision for rural revitalization [4]. Rural revitalization evaluation can keep track and make adjustments to the strategy’s progress. Using the rural revitalization evaluation model, it is possible to track the development of the rural revitalization strategy, including whether progress has been made in the five areas of “prosperous industry, livable ecological, civilized rural traditions, efficient governance, and prosperous life.” Through monitoring the rural revitalization process, the problems existing in the rural revitalization process can be found in time to implement targeted policies and correct the deviations in the development. Rural revitalization evaluation helps classify and guide rural revitalization strategies in various regions. The rural revitalization strategy must proceed from the actual situation of each region, and it needs to be promoted according to local conditions and classified. The rural revitalization evaluation can rank the existing rural conditions according to the index evaluation scores of various regions to scientifically measure the progress and grasp the actual situation of rural revitalization in various regions [5].

BP neural network, a multi-layer feedforward network trained through backpropagation algorithm, and genetic algorithm, a search algorithm that simulates natural selection and genetic mechanisms. This hybrid method can more effectively solve complex problems in rural revitalization evaluation. There are certain limitations in the evaluation of rural revitalization in existing research. Some studies may rely solely on traditional statistical methods or a single machine learning algorithm, which may not fully address the complexity and non-linear relationships in rural revitalization evaluation. By introducing a hybrid method of BP neural network and genetic algorithm, we can better capture these complexity and nonlinear relationships, thereby providing more accurate and comprehensive evaluation of rural revitalization.

II. Literature Review

A. Rural Revitalization Strategy

1) Rural revitalization strategy: The proposed and improved rural revitalization strategy is based on rural construction theory and practice [6]. Regarding national development, the stance of “agricultural, rural areas, and farmers” must be spelled out. The peasant masses are crucial to the process of national revolution, construction, and development, and peasant masses must constantly be taken into account in national development [7]. “Three Rural” work is not only related to rural areas’ development but also to social stability and the realization of national goals. The government should give political guarantees for the healthy growth of “agricultural, rural areas, and farmers” and should direct the development and construction of rural areas. The government should emphasize agricultural production and policy reform, promote agricultural and rural modernization, and improve the training of rural grassroots party groups and talent management [8].

2) The scientific connotation of a rural revitalization strategy: They were all development plans put forth by the state in reaction to the current domestic situation at the time, and the “rural revitalization strategy” was founded on “creating a new socialist countryside” [9]. The introduction of the rural revitalization plan is a necessary condition for the growth of the times, indicating that rural development has reached a new stage and that a new era based on the strategy is about to begin [10].

Rural revitalization is a three-dimensional security strategy that encompasses economic, ecological, cultural, social governance, and other components of the entire revitalization rather than just one or a few areas of revitalization [11]. First is adhering to the policy orientation of prioritizing the development of agriculture. Agricultural development must focus on high-quality development requirements, stabilize grain production, and ensure the absolute security of national rations. Agricultural development must adhere to the word “excellent” and quality first. Social development cannot simply pursue scale and speed but should seek sustainability. The level of development varies greatly in different regions. It is necessary to respect the differences, diversity, and regional characteristics of agricultural and rural development, implement classification, and adapt to local conditions [12]. Whether the prerequisites for the priority development of agriculture and rural regions can be accomplished in practice depends on whether the objectives of agricultural and rural modernization and national modernization can be achieved. Second, clarifying the general guidelines for the rural rejuvenation approach is the second step. Third, industrial revitalization is the focal point and critical component of rural revitalization. Developing modern agriculture, promoting the integrated growth of primary, secondary, and tertiary industries, and establishing a rural industrial system is crucial for the success of rural industries. The country needs to keep developing agriculture that is good for the environment now and in the future. Fourth, comprehensively deepening rural reforms are necessary for rural rejuvenation. Reform is necessary for rural revival to promote vitality. Further adjustments are required to ensure the agricultural structure is optimized and to assume the integrated growth of primary, secondary, and tertiary industries in rural areas.

B. Deep Learning Model

1) Deep learning: Deep learning, a machine learning algorithm, makes multiple multilayered, nonlinear modifications to data to abstract it [13]. A multi-level machine learning approach called “deep learning” is built on learning representations to model the intricate relationships between data [14].

Deep learning builds a hierarchical model structure matching the human brain (attribute categories or features) by modeling the brain's nervous system with a rich hierarchical structure and extracting the input data level by level to construct more abstract higher-level representations [15].

2) BP Neural Network Model

a) Structure and characteristics of BP neural network: A BP neural network is constructed with an input layer, several hidden layers, and an output layer [16]. The output signal from the second layer serves as the input signal for the third layer, the excitation mode unit of each node output by the input layer serves as the input for the first hidden layer, etc. [17]. Fig. 1 depicts a BP neural network with a three-layer design and one hidden layer.

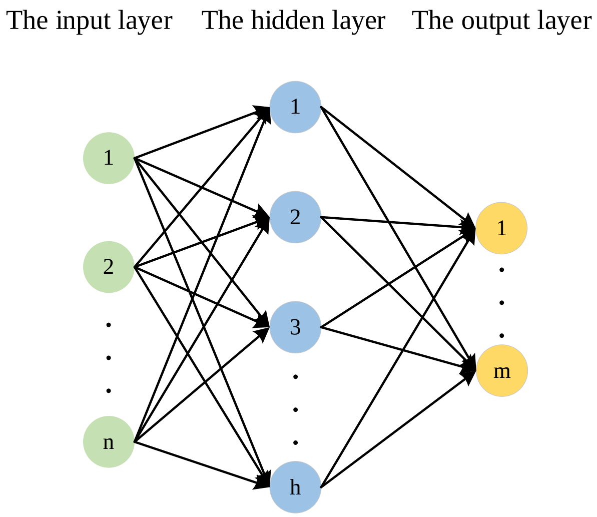


Fig. 1. Three-layer BP network model structure.

b) BP neural network learning algorithm: The mathematical relationship between signals of each layer is [18]:

$$o_k = f(net_k), k = 1,2,\ldots,l \quad (1)$$

$$net_k = \sum_{j=0}^{m} w_{jk}\, y_j, k = 1,2,\ldots,l \quad (2)$$

$$y_j = f(net_j), j = 1,2,\ldots,l \quad (3)$$

$$net_j = \sum_{i=0}^{n} v_{ij}\, y_i \quad j = 1,2,\ldots,m \quad (4)$$

The derivatives of *f(x)* in the above equations are all S-functions, and the derivatives of *f(x)* are:

$$f'(x) = f(x)[1 - f(x)] \quad (5)$$

The mean square error of the actual output of the network to the desired output is:

$$E = \frac{1}{2}\sum_{k=1}^{l}(d_k - o_k)^2 \quad (6)$$

Then, the amount of weight adjustment in the output and hidden layers of the network is:

$$\Delta w_{jk} = \eta(d_k - o_k)o_k(1 - o_k)y_j \quad (7)$$

$$\Delta v_{ij} = \eta(\sum_{k=}^{l} \delta_k^o w_{jk})y_j\ (1 - y_j\ )x_i \quad (8)$$

$$\delta_k^o = (d_k - o_k)o_k(1 - o_k) \quad (9)$$

The η is the scaling factor, which represents the learning rate in the network training.

Supposing the BP network has *m* implicit layers. In that case, the number of nodes in the implicit layer is represented by m_1, m_2 ,..., m_h, and the output of the hidden layer is represented by y_1, y_2,..., y_h, then the amount of weight adjustment for each layer is:

Output layer: $\Delta w_{jk}^{h+1} = \eta(d_k - o_k)o_k(1 - o_k)y_j^h \quad j = 0,1,2,\dots,m_h; k = 1,2,\dots,l$; the h-th hidden layer: $\Delta v_{ij}^h = \eta(\sum_{k=1}^{l} \delta_k^o w_{jk}^{h+1})y_j^h(1 - y_j^h)y_i^{h-1} \quad i = 0,1,2,\dots,m_{h-1}; j = 1,2,\dots,m_h$; first hidden layer: $\Delta v_{pq}^1 = \eta(\sum_{r=1}^{m_2} \delta_r^2 w_{qr}^2)y_q^1(1 - y_q^1)x_p \quad p = 0,1,2,\dots,n; q = 1,2,\dots,m_1$

From the previous, it can be observed that in the BP learning algorithm, the input signal of each layer, the error signal of each layer's output, and the learning rate all influence how much the weights of each layer are adjusted [19].

C. *Genetic Algorithm*

1) Basic concept of genetic algorithm: A method for global optimization known as a "genetic algorithm" was developed by mimicking biological processes like genetic evolution [20]. It is characterized by group search and mutual exchange of information between groups. The genetic algorithm search does not depend on the gradient problem. So, it has excellent robustness and a capability for worldwide search. Additionally, complex nonlinear problems that are challenging to solve using conventional search techniques can be solved using evolutionary algorithms. Genetic algorithms use many concepts in biology, such as gene chain code, population, crossover, variation, fitness, and selection [21].

2) Flow of genetic algorithm: Like neural networks, genetic algorithms are capable of nonlinear mapping and can solve complex optimization problems, such as multi-objective and nonlinear optimization problems. In addition, a genetic algorithm is an approximation algorithm. The mathematical model of the genetic algorithm is shown in Fig. 2.

3) Design and implementation of genetic algorithm

a) Coding method: Genetic algorithms operate on individuals in a population to accomplish optimization, and they can only deal with individuals through gene chain codes [21]. Therefore, individuals need to be transformed into the form of gene chain codes before using the genetic algorithm. This process is called coding. When designing the encoding scheme, three issues are often considered.

Completeness: All points in the problem space can be found in the expression space, i.e., all possible solutions in the problem space can be transformed into gene chain codes. Soundness: all points in the expression space find their counterparts in the problem space, i.e., each gene chain code corresponds to a possible solution. Non-redundancy: there should be a one-to-one correspondence between the problem and expression spaces.

b) Design of fitness function: The fitness function's design is the foundation for the genetic algorithm's optimization search and directly impacts how well it works. The design of the fitness function is dictated by how the problem will be solved, and it must have a positive outcome. The following three aspects of the fitness function are explained from the fitness function's design method, the fitness function's adjustment, and the influence of the fitness function on the genetic algorithm [22].

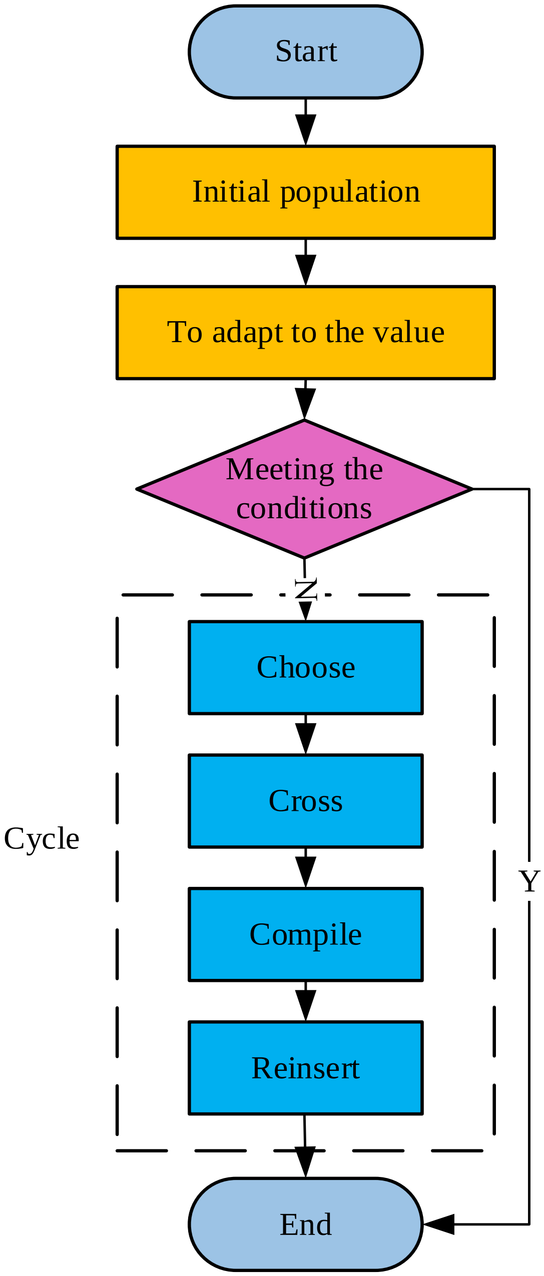


Fig. 2. Mathematical model of genetic algorithm.

i) The fitness function's design process. The fitness function's design must take into account two factors. First, the genetic algorithm seeks the smallest value rather than looking for the most significant value of the goal function of g(x). Second, the genetic algorithm ranks the individual's fitness based on this to determine the selection probability so that the fitness function must be positive. How to map the objective function into the maximum form and ensure the non-negativity of the fitness function is the key to the design of the fitness function. The function can be multiplied by -1 to transform the minimum value problem into a maximum value problem. However, this does not guarantee the non-negativity of the fitness function. For this case, the following approach can be taken to transform the objective function *g(x).*

$$f(x) = \begin{cases} C_{max} - g(x), & g(x) < C_{max} \\ 0, & others \end{cases} \quad (10)$$

The C_{max} in the above formula is usually taken as the maximum value of *g(x)* in the process of evolution. If *g(x)* is a non-negative function, *f(x)=1/g(x)* conversion can also be used.

When the genetic algorithm finds the maximum value of the objective function *g(x),* to ensure the non-negativity of the fitness function, the conversion can also be performed:

$$f(x) = \begin{cases} C_{min} + g(x), & C_{min} + g(x) > 0 \\ 0, & others \end{cases} \quad (11)$$

In the above formula, C_{min} is usually taken as the evolutionary process's minimum value of *g(x).*

ii) Adjustment of the fitness function. Some abnormal individuals often appear when using the genetic algorithm to optimize the population. When the number of abnormal individuals is too much, the more competitive they will be, which will lead to the phenomenon of convergence before the optimization is full. Therefore, it is crucial to reduce the competitiveness of these abnormal individuals. Reducing the competitiveness of abnormal individuals can be achieved by deflating the fitness function, and this deflation becomes the adjustment of the fitness function. The adjustment of the fitness function is the key to ensuring that good individuals are selected, and the commonly used adjustment methods are linear adjustment and power function adjustment.

The following formula can express linear adjustment:

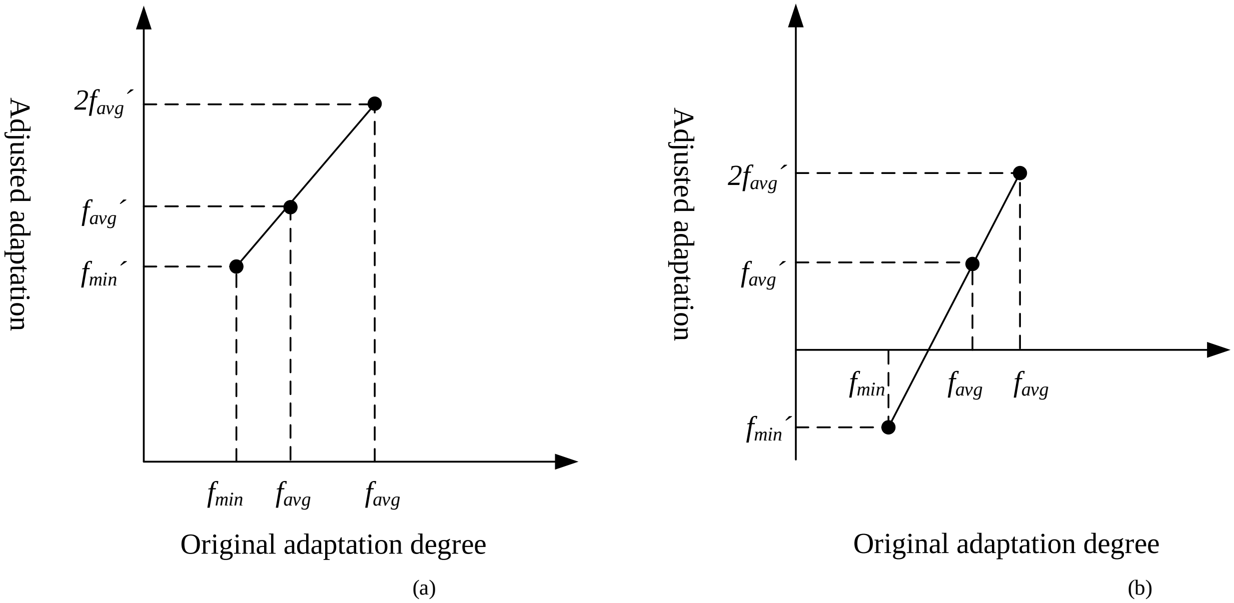
$$f(x)' = af(x) + b \quad (12)$$

In the formula above, *f(x)* represents the original fitness function, *f(x)'* represents the modified fitness function, and the coefficients a and b are selected to satisfy the following conditions: (1) The adjusted fitness must have the same mean value as the original fitness. (2) The highest value of the modified fitness function must be a predetermined multiple of the original fitness function's mean value. That is,

$$f_{max}(x)' = Cf_{avg}(x) \quad (13)$$

The *C* is a replication number set to obtain the optimal individual, and usually, *C* can take a value between 1.2 and 2.0.

Condition (1) is proposed to ensure that, on average, individuals in each population can produce the desired offspring in subsequent selection treatments. The proposed Condition (2) would limit the number of offspring generated by the person with the highest initial fitness. It should be noted that the adjusted fitness values may have negative values. The excessive scaling of coefficient C mainly causes the negative value to the original fitness function. Fig. 3(a) shows the result of the standard adjustment, in which the fitness values of a few abnormal individuals are scaled down, and the others are scaled up, and there are no negative fitness values. Fig. 3(b) shows the unreasonable adjustment. The fitness of abnormal persons is significantly lower than the mean value of fitness $f_{avg}(x)$ and the maximum value of fitness f_{max} *(x).* When the linear adjustment is used to pull apart $f_{avg}(x)$ and $f_{max}(x)$, there will be negative fitness values. When the coefficient *C* cannot meet the requirement of fitness adjustment, the original fitness minimum $f_{min}(x)$ can be mapped to the adjusted fitness minimum and make $f_{min}(x)' = 0$, provided that $f_{avg}(x) = f_{avg}(x)'$ is still guaranteed.



(a) (b)

Fig. 3. (a) Result of standard adjustment. (b) Unreasonable adjustment.

Power adjustment: The adjustment is to do k times power treatment on the original fitness function *f(x)*, that is, *f(x)' =f*$_k$*(x)*, and the value of *k* is related to the solution of the problem to be solved, and it can be corrected on demand in the process of the algorithm.

iii) The influence of the fitness function on the genetic algorithm

First, the genetic algorithm's selection operation directly affects how the fitness function is designed. Second, the fitness function specifies the genetic algorithm's iteration stopping condition. There is no specific theory about the genetic algorithm iteration stopping condition. Generally, the iteration stopping condition is when the fitness function reaches the maximum or suboptimal value. However, the maximum and suboptimal values are uncertain in many optimization problems. In such cases, the algorithm iteration is usually terminated when the evolution of the population of individuals tends to a steady state.

c) Selection of genetic operators: The genetic algorithm makes up of three fundamental operators—selection, crossover, and mutation. The selection operator plays a crucial part in the genetic algorithm, with the fitness proportion technique and the expectation value method constituting the most overall selection strategies [23]. The most used selection algorithm is the fitness proportion technique. Each person's fitness in this approach relates to how likely they will be chosen. If the starting population size is n and each individual's fitness score is f_i, the likelihood that an individual will be chosen is P_i.

$$P_i = \frac{f_i}{\sum_{j=1}^{n} f_i} \tag{14}$$

The expectation ratio method calculates the number of individuals' next generation expected to survive based on their fitness values. This method can avoid the phenomenon that good individuals are eliminated and abnormal individuals are selected in the fitness proportion method. The following formula can describe the expected value proportion method.

$$M = \frac{f_i}{\bar{f}} = \frac{nf_i}{\sum f_i} \tag{15}$$

The *f* is the fitness function's average value.

D. Optimization of Neural Networks by Genetic Algorithm

1) Optimizing network connectivity: The BP learning method is the most traditional way to gain the connection rights of the BP neural network. This algorithm's drawbacks include sluggish training speed and frequent slips into local minima. This issue can be significantly resolved by employing the genetic algorithm. The steps of the genetic algorithm to improve the connection rights of the BP neural network are as follows.

a) Determining the encoding scheme. The encoding method has binary encoding and real encoding. Binary coding is simple but not intuitive, and the accuracy is not high; Real coding is very intuitive and accurate. Therefore, the real coding method is commonly used to encode the connection weights.

b) Determining the fitness function. In genetic algorithms, fitness functions can be defined as f= C-e, where C is a constant and e is the sum of the squares of errors. There are many ways to select the fitness function, including the relationship with energy function, evolution time, and network complexity, as long as the fitness function is non-negative.

c) Genetic manipulation. In a genetic algorithm, genetic operation mainly refers to selection, crossover, and variation. The advantage of genetic operation is that it can realize a global search for complex nonlinear functions. However, when gradient functions are easy to obtain, they should be used as much as possible. The local optimization capability of the BP algorithm is relatively robust. Thus, adding a genetic algorithm with global optimization capability can modify the BP algorithm's flaws.

2) Optimizing network structure: The connection patterns and weights between the nodes are the two primary components of a neural network's structure. The following are the main steps in the genetic algorithm optimization of the neural network structure.

a) Randomly generate n different structures and encode each structure. Different codes correspond to different structures.

b) Training the structures in the individual set with different initial weights.

c) Determining the fitness of individuals with the results of training.

d) Selecting the individuals with higher fitness for the next generation.

e) Crossover and mutation of the population to produce a new generation.

f) Repeat the process of (2)-(5) until the network structure meets the requirements.

E. Establishment of the GA-BP Model

Optimizing BP networks with genetic algorithms mainly includes three aspects: optimizing connection weights, optimizing network structure, and optimizing learning rules [24]. However, the theory of network structure optimization and learning rule optimization is still immature and difficult to implement. This paper focuses mainly on the research and implementation of genetic algorithms to improve the weights and thresholds of BP networks [25].

A genetic algorithm encodes the connection weights and thresholds in the BP network in order to maximize the neural network's connection weights. Finally, genetic operators are employed, including selection, crossover, and variation [26]. The genetic output results are utilized as the initial weights and thresholds of the BP network to generate the GA-BP prediction model, and the GA-BP model is trained to attain the needed level of accuracy [27]. The specific operation flow is shown in Fig. 4.

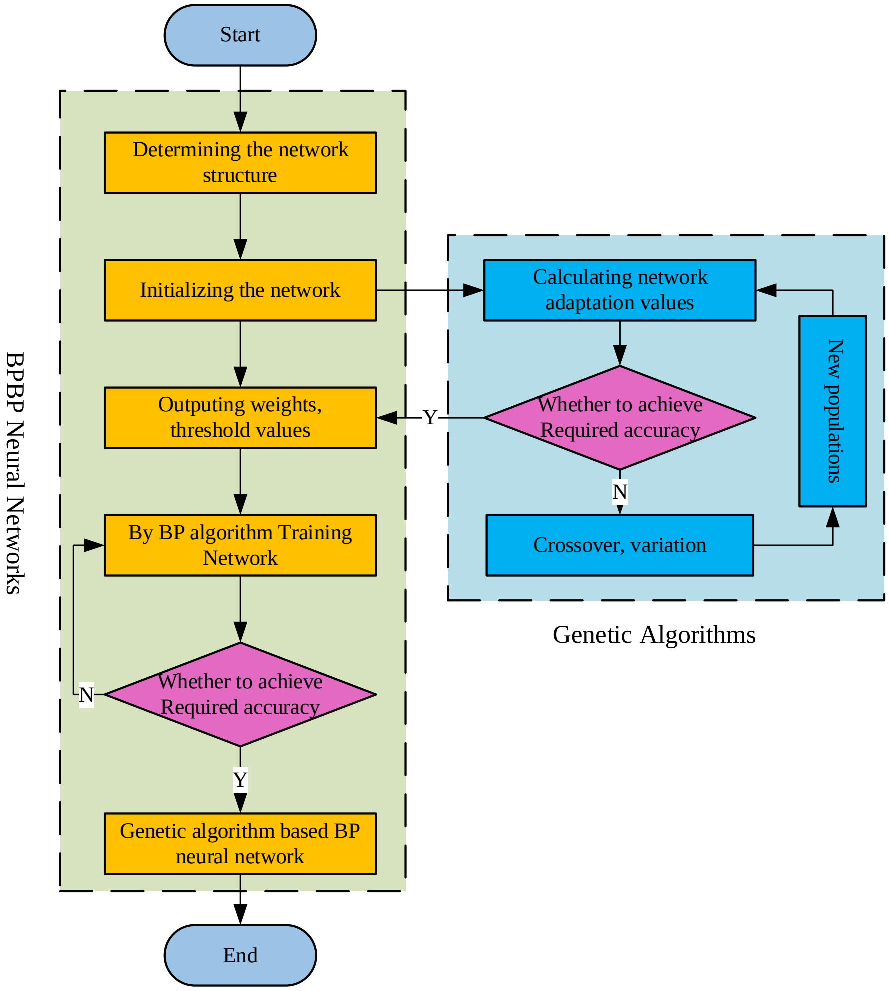

Start
Determining the network structure
Initializing the network
Outputing weights, threshold values
By BP algorithm Training Network
Whether to achieve Required accuracy
N
Y
Genetic algorithm based BP neural network
End
BPBP Neural Networks
Calculating network adaptation values
Whether to achieve Required accuracy
Y
N
Crossover, variation
New populations
Genetic Algorithms

Fig. 4. GA-BP model.

III. Method

A. Establishment of Rural Revitalization Evaluation Index System

This paper establishes the following evaluation index system based on the Specification for the Construction of Beautiful Countryside in the New Era. There are four primary indicators and 15 secondary indicators. The primary indicators are the basis of industrial development, ecological environment, civilization management, and living standards.

B. Determination of the Evaluation Level of Rural Revitalization

This paper uses the Delphi technique to measure how rural revitalization has affected the research object to measure the situation accurately. The Delphi technique is simply a confidential letter consultation process. Generally, it involves gathering expert opinions on the problems that need to be forecasted, sorting, induction, and statistics, followed by anonymous feedback to the experts. This process is repeated until all expert opinions are in agreement.

C. Construction of GA-BP neural network model

1) Determination of the number of neurons in the input and output layers: The contribution of the BP network to this experiment is the second indicator of the rural revitalization evaluation index. Therefore, there are fifteen neurons in the input layer and one neuron in the output layer, which reflect the assessment value of the results of rural revitalization.

2) Determination of the number of hidden layers and the number of neurons: Nonlinear recognition capabilities of the BP network are caused mainly by the existence of one or more hidden layers between the input and output layers. Through the addition of more hidden layers, accuracy can be enhanced and error reduced. However, it also increases the network’s complexity and training time, as well as the training error of the network weights. Consequently, there are two methods for improving accuracy: increasing the number of hidden layers and the number of hidden layer neurons. The optimal number of neurons for the buried layer cannot be calculated with absolute confidence on a theoretical level. The selection of the number of inferred layer neurons is also compatible with specific empirical formulations, such as Formula (16). The estimated number of implied layer neurons derived from the formula can serve as the starting point for the trial-and-error process.

$$m = \sqrt{n+1} + \alpha \tag{16}$$

Fig. 5 shows the correlation coefficients and mean square error (MSE) obtained by training the three-layer BP neural network with the number of neurons in the hidden layer ranging from 5 to 15.

According to this study, when there are 12 neurons in the hidden layer of a three-layer BP network, the correlation coefficient is at its highest, and the MSE is at a more desired level. The correlation coefficient is at its lowest when the number of neurons in the hidden layer is 13, and the correlation coefficient is even negative during training. Theoretical investigation indicates that the average number of neurons in the buried layer is between 1 and 2. After repeated training, two BP number neural networks were initially identified: BP networks with one hidden layer and two hidden layers. Fig. 6 depicts the output of the correlation coefficients and mean square error (MSE) after training these two networks ten times.

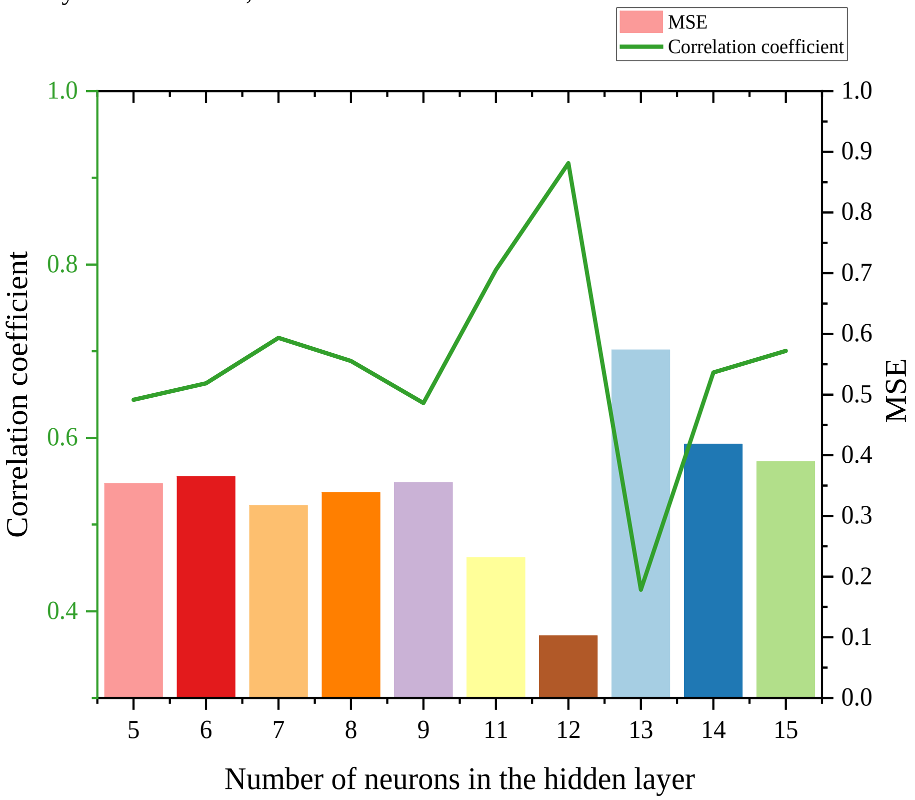
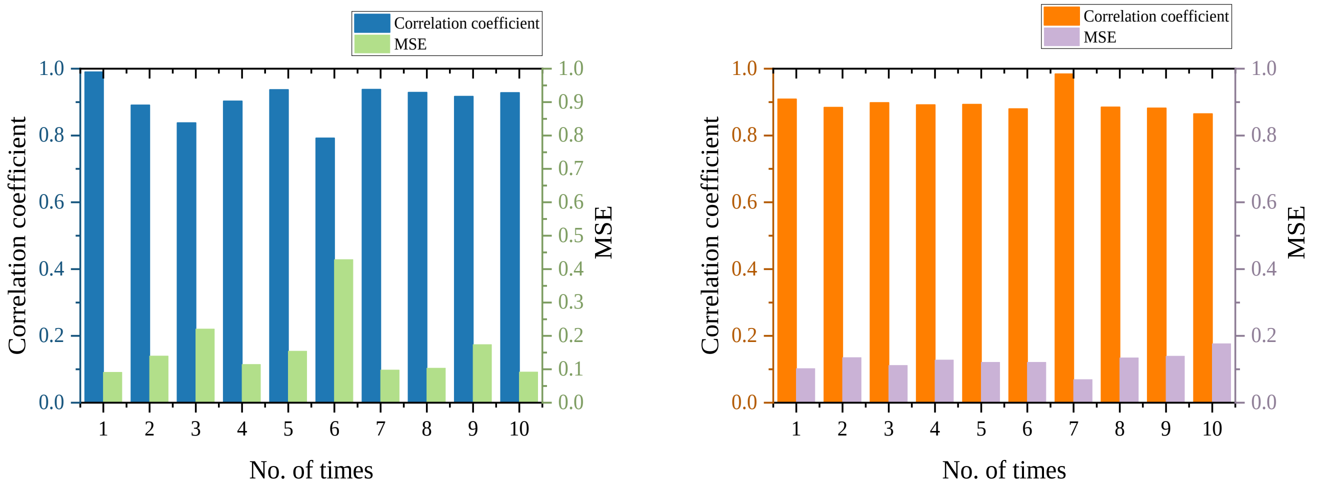


Fig. 5. Training of three-layer BP neural network.



One hidden layer of BP neural network

Two hidden layers of BP neural network

Fig. 6. Correlation coefficients and MSEs of BP networks with different numbers of hidden layers.

The unpredictability of the BP network's initial weights is evident in the fact that the outcomes of each training are not the same and that there is a significant amount of variability in the training results. It is found that the differences in training error, correlation coefficient, and MSE between the BP network with one hidden layer and the BP network with two hidden layers are not much. Moreover, compared with the BP network with one hidden layer, the network structure with two hidden layers is more complex and takes longer to train. The fact that the results of each training are different and that there is a sizable level of variability in the training results shows how unpredictable the starting weights of the BP network are.

D. Optimization of Weights and Thresholds by Genetic Algorithm

1) Determining the genetic algorithm population: In genetic algorithms, the size of the population directly affects the global optimization characteristics of the genetic algorithm. In general, the larger the population size, the higher the diversity of the population, and the less likely the algorithm will fall into local minima during optimization. The population size is generally set between tens and hundreds. The calculation speed is also considered in the selection of population size. Combining these two factors, in this experiment, the number of genetic algorithm populations is 40.

2) Determining the genetic algorithm variation probability: In the genetic algorithm, the variation probability's size directly affects the algorithm's convergence and the final solution's performance. The larger the variation probability, the higher the diversity of individuals, but an increase in the variation probability reduces the convergence of the network, leading to a reduction in the final solution's performance. In engineering applications, the variation probability size usually ranges from 0.001 to 0.1. In this experiment, the probability of the genetic algorithm was determined to be 0.05.

3) Training of the genetic algorithm: The fact that each training produces a new set of outcomes and a considerable degree of variability in the training results demonstrates how unpredictable the BP network's beginning weights are. The genetic algorithm of this experiment is selected 100 times, and the MATLAB genetic algorithm toolbox is applied to train the samples. The error sum of the squares curve and fitness value curve during training are shown in Fig. 7. With the increase in training times, the sum of error squares becomes smaller and smaller, and the fitness value increases gradually. The larger the fitness value, the higher the sample's fitness to the environment is.

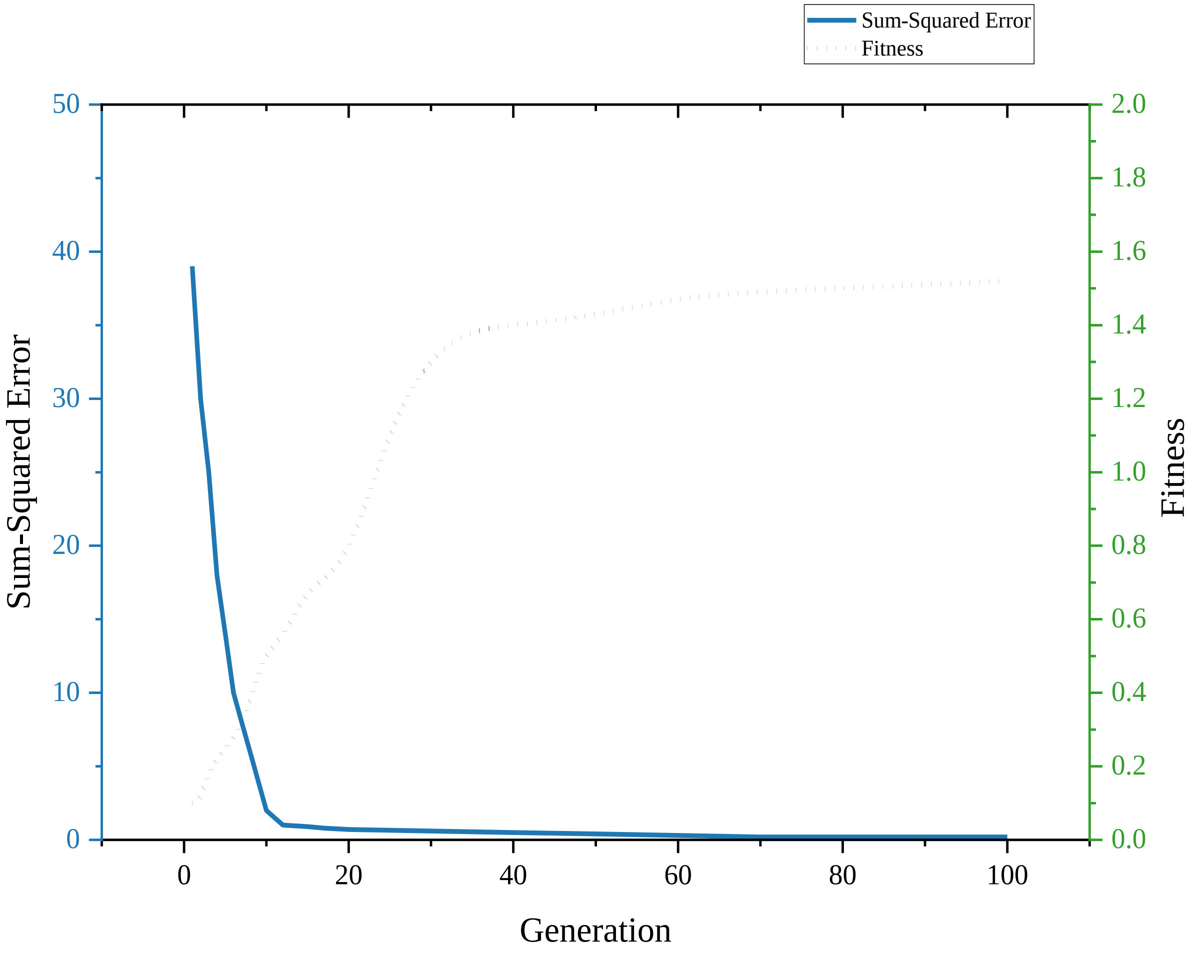


Fig. 7. Error sum-of-squares curve and fitness curve.

IV. Results

A. Selection of Training Samples

In this work, 30 samples were selected: 20 were used for training the GA-BP model, and 10 were used as test samples. The evaluation indexes in the samples were used as the input of the GA-BP model, and the model's output was the prediction of the rural revitalization evaluation at this time. Finally, the prediction accuracy of the GA-BP model could be obtained by comparing the predicted value with the actual value.

B. Evaluation of GA-BP Prediction Model

This paper used three indicators of convergence, accuracy, and stability. Convergence was judged based on the number of Epochs of steps in the network training process to determine the convergence speed. Different networks converge faster with fewer steps when they reach the same training goal; conversely, convergence is slower with more steps. Accuracy was determined by the relative error between the test simulation output value and the desired output value of different networks to determine the accuracy of the output results obtained by testing the trained network. Where, relative error = (test simulation output value - desired output) / desired output × 100%. The stability of the network was further judged from the macroscopic point of view by calculating the mean square error (MSE) of the test output of different networks based on the error between the test simulation output and the expected output.

The convergence curves of the GA-BP prediction model are shown in Fig. 8. It can be found that the loss function of the GA-BP prediction model converges to stability and achieves the training goal after 400 times of training.

In this article, the GA-BP network model was evaluated, and the test simulation output results are depicted in Fig. 9. It can be seen that the GA-BP prediction model can reduce the percentage error of predicted samples to less than 4% and that the prediction error of some samples is nearly zero.

The GA-BP prediction model was trained ten times, and the percentage error, correlation coefficient, and mean square error (MSE) of the test samples are output, as shown in Fig. 10.

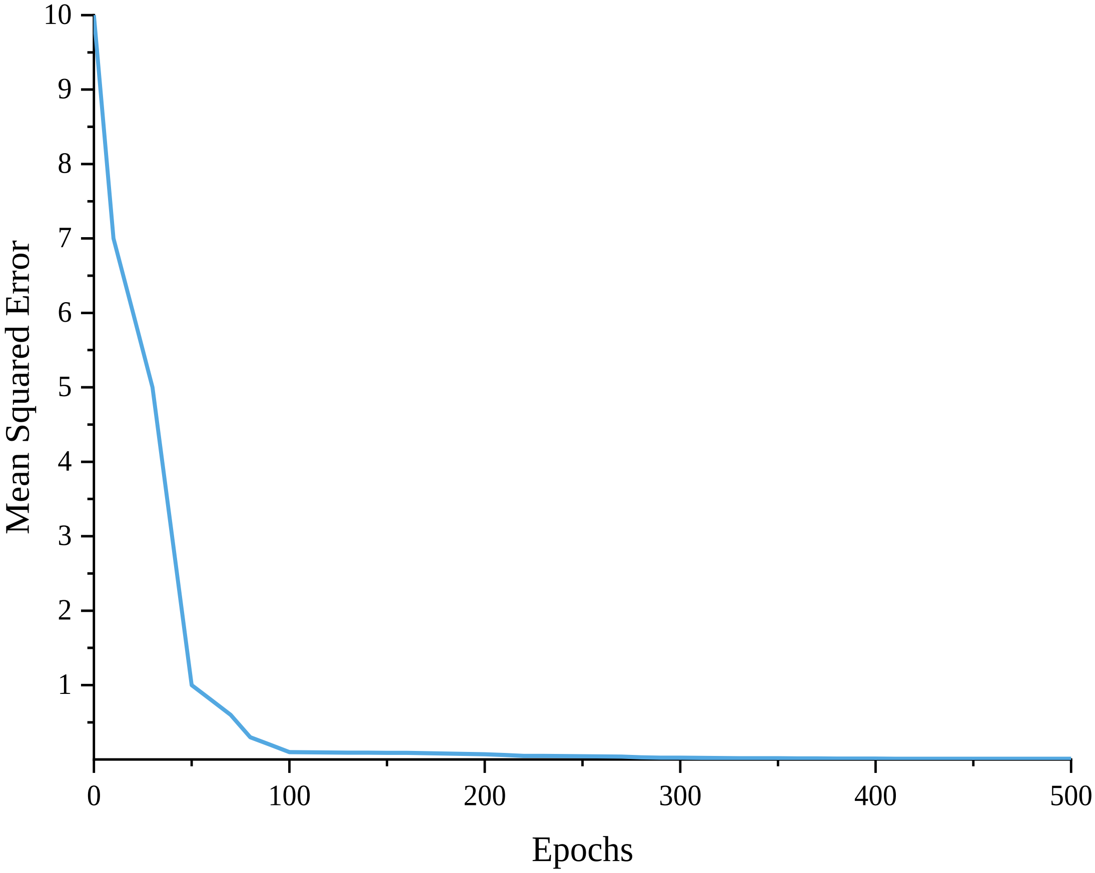


Fig. 8. Convergence of the GA-BP prediction model.

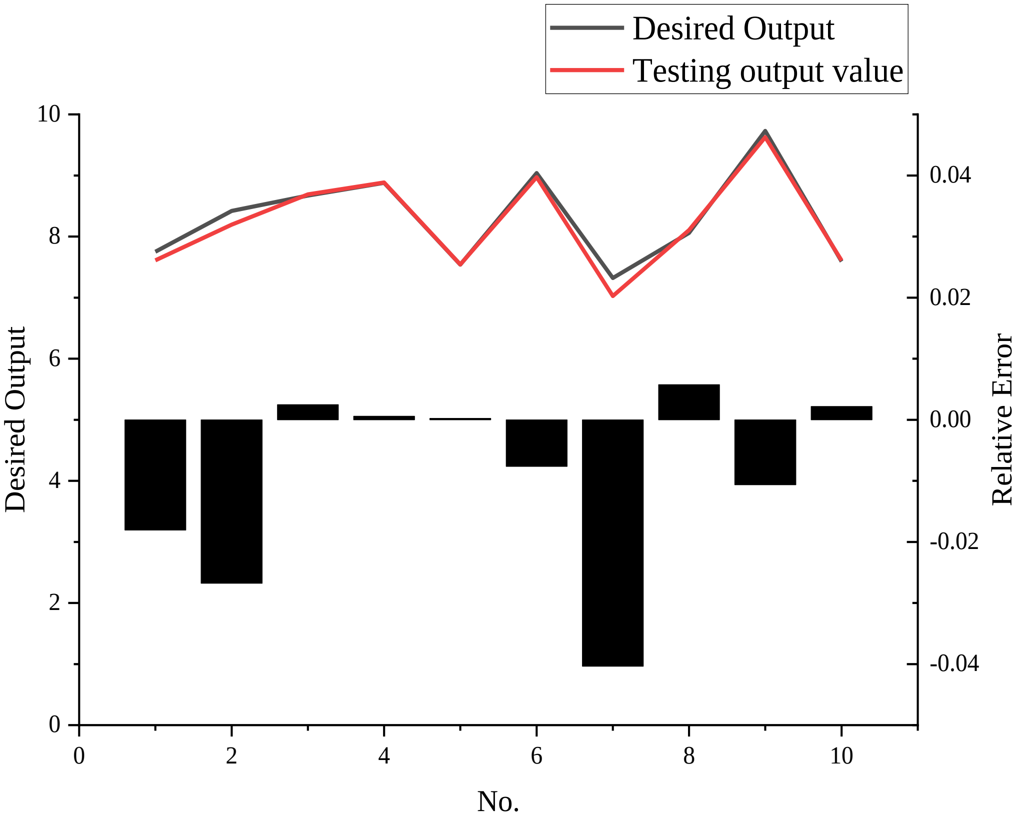


Fig. 9. Simulation results of GA-BP neural network for test sample data.

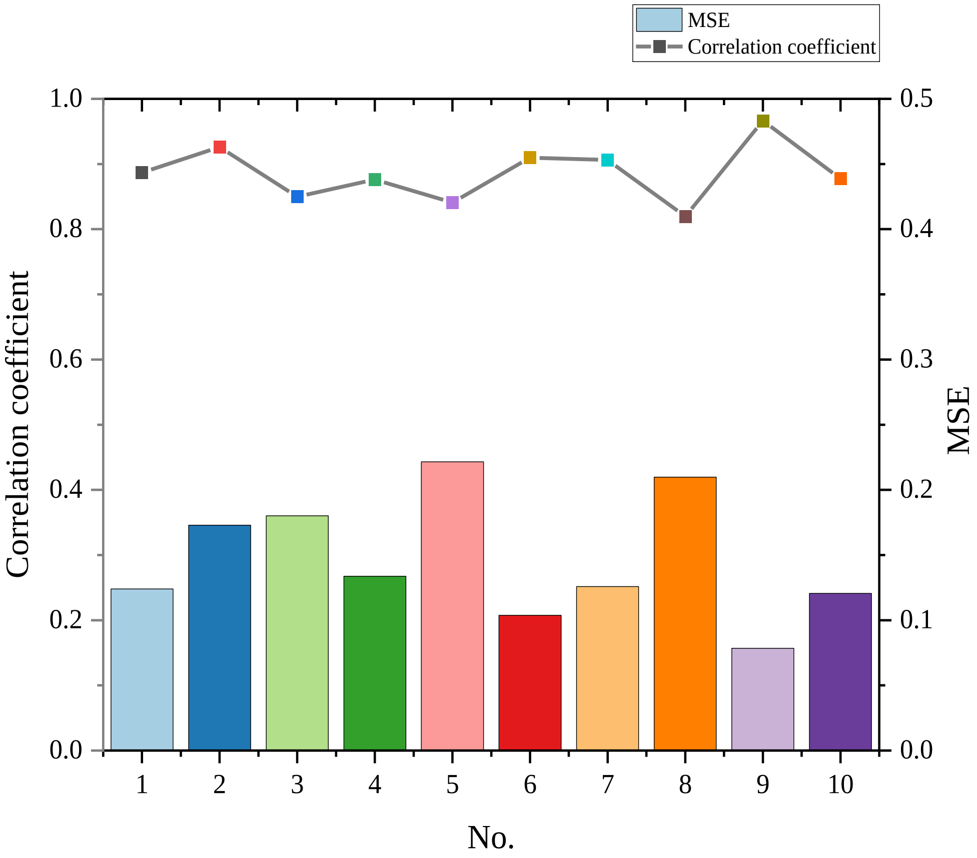


Fig. 10. Prediction of samples by GA-BP model.

V. Discussion

There are many factors affecting rural revitalization, and this paper only designs the evaluation index system based on the existing policy situation and literature research in China. The relevance and applicability of the evaluation indexes and the allocation of index weights are issues that need further study in evaluating rural revitalization. In addition, due to the difficulty of obtaining evaluation data, this paper only selects relevant subjective evaluation data obtained in actual work to train and test the neural network, which is insufficient in the sample data. The information reflected by the sample is not comprehensive enough. Further research is needed to find a general, efficient, or accurate parameter setting method; for the shortcomings of the traditional genetic algorithm, which is prone to premature maturity and slow convergence, other methods can be used to improve the traditional genetic algorithm.

VI. Conclusion

This research conducted an extensive and systematic study on the evaluation of rural revitalization by the consultation of several pieces of literature, given the circumstances of rural revitalization strategy. This article established the rural revitalization evaluation index system according to pertinent policies and documents. The GA-BP neural network model was built using deep learning theory. The GA-BP neural network model addressed the BP neural network's training process drawbacks, including its slow pace, ease of dipping below the local minimum value, and reliance on the initial weight. The rural revival was assessed and predicted using the GA-BP neural network model. The findings demonstrated that the GA-BP neural network model had rapid convergence, accuracy, and stability in rural rejuvenation's evaluation and prediction abilities, demonstrating its high applicability in these areas.

Competing of Interests

The authors declare no competing of interests.

Authorship Contribution Statement

Songmei Wang: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Min Han: Methodology, Software, Validation.

Data Availability

On Request

Declarations

Not applicable

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Sound Classification for Javanese Eagle Based on Improved Mel-Frequency Cepstral Coefficients and Deep Convolutional Neural Network

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***Abstract*—The Javanese Eagle is a rare and protected animal in Indonesia. These animals only live in a few species and are threatened with extinction. These birds need to be bred to avoid extinction. One form of communication between the Javanese eagles and each other is the sound of their tweets. These tweets can be studied and classified to conserve endangered animals. This study will classify the sound of the Javanese Eagles for the benefit of animal conservation. Data in the form of voice tweets will be classified. This classification uses algorithms from improved MFCC (Mel-Frequency Cepstral Coefficients) and Deep Convolutional Neural Network. The result of this study was to classify the sound of the Javanese Eagle from the lack of food or drink, the normal tweets state of the bird, and to find out the Javanese Eagle in finding a partner. This research has been carried out by comparing the CNN architecture with AlexNet and VGGNet models and various combinations of training, validation, and test data. The best model dataset underwent division into 80% for training, 10% for validation, and 10% for testing. Training and testing of both IMFCC and VGGNet models occurred using the same dataset. During training, VGGNet achieved 100% accuracy, while testing yielded 99%. ROC Curve: 'Normal' AUC 0.996, 'Looking for Partner' AUC 1.000, 'Looking for Food' AUC 0.996. This study aids Javanese Eagle conservation, crucial for preventing extinction at conservation sites.**

Keywords*—Improved MFCC; deep convolutional neural network; Javanese eagle sound; sound classification

I. Introduction

The Javanese Eagle (*Nisaetus Bartelsi*) is a rare and protected animal in Indonesia. The Javanese Eagle existence is increasingly rare because of the eruption of Mount Merapi, which caused the death of many Javanese Eagles and it only lays 1 to 2 eggs per year. In addition, many illegal hunters hunt these birds to sell and make a profit [1]. Even though in 1990, eagles were protected by the government, there are still many who trade eagles illegally [2]. These animals only live a few species globally and are threatened with extinction [3, 4]. The Javanese Eagle is one of the animals that are conserved in zoos and nature reserves. These birds need to be bred to avoid extinction [5]. Especially in zoos, caretakers need to pay attention to the needs of these birds, especially in maintaining a balance nutrition. Because, balanced nutrition will keep Javanese eagles to survive. However, sometimes they cannot understand the Javanese Eagle's needs quickly. Javanese eagles usually use their tweet to code their environment to find food or before eating other animals. From the tweet sound, it can be identified the conditions and needs of the Javanese Eagles. The voice of this tweet is very distinctive and very specific which can be heard [6, 7].

In helping to preserve the Javanese Eagle, research is needed to identify the needs of the Javanese Eagles. The chirping sound of this Javanese Eagle can be studied and classified to help in the conservation of endangered animals. With the tweets studied by the proposed technique and verified by experts, can know the basic needs of the bird especially in searching for prey. This research will develop a Javanese Eagle’s sound classification technique that will classify the sound of the Javanese Eagle into lack of food or drink, knowing the Javanese Eagle in search of partner, and normal state of bird tweets through combination of algorithms from Mel-Frequency Cepstral Coefficients (MFCC) [8] and Deep Conventional Neutral Network [9, 10, 11, 12, 13]. The data from this study were taken from zoos and nature reserves in Indonesia such as the Ragunan Zoo, PSSEJ, and the Bogor Botanical Garden. The sound that was taken and use as a data are validated by experts. Data in the form of voice tweets will be classified.

MFCC is a feature extraction that produces features in the form of cepstral coefficient parameters. Feature extraction Mel Frequency Cepstral Coefficient (MFCC) converts sound waves into several types of parameters such as the cepstral coefficient which represent the audio file. In addition, Improved MFCC generates feature vectors that convert voice signal into several vectors for speech recognition. This signal is known as spectrogram. Convolutional Neural Network (CNN) is the development of Multilayer Perceptron (MLP) which is designed to process two-dimensional data. CNN is included in the type of Deep Neural Network because of its high network depth and widely applied to image data. The sound image formed from the MFCC model can provide a specific picture so that CNN can train properly so as to produce an accurate model. Before being processed using CNN, the Javanese eagle’s sound needs to be converted to a spectrogram first. The existence of this spectrogram provides a significant difference from the presence of audio in a tweet. Spectrograms provide higher accuracy in training that audio signals trained in digital form. The Improved MFCC and followed by CNN in deep learning architecture was designed to classify the Javanese Eagle’s voice. Javanese eagle sound classification was used to identify whether the Javanese eagle is lacking of food or drink, finding a partner, or it is a normal tweet of bird. The result of this research was used to help the bird's caretaker to better understand the basic needs of the Javanese Eagle.

The combination of signal processing and deep learning has the potential to reveal the complex layers of meaning hidden within the vocal repertoire of the Javanese Eagle. By combining different methodologies, the objective was to classify the tweets of the Javanese eagle into specific categories: regular sounds representing their daily activities, sound indicating their hunger and search for food and sound expressing their desire for a mate, reflecting the intricate social dynamics of these magnificent birds of prey.

The output of this research has helped to protect Javanese eagle birds from extinction. In this research, the needs of Javanese eagle can be identified from the sound of their chirping. This research created an application that can differentiate the sound of the tweets of the Javanese eagle. This research is expected to have a major impact in the caring for the existence of the Javanese eagle by providing what is needed quickly. By providing caretakers and conservationists with a tool to swiftly identify and respond to the needs of the Javanese Eagle, the study contributes to the ongoing efforts to protect this species from extinction. Developing an application capable of distinguishing between different tweet sounds holds significant promise for enhancing the management and conservation of the Javanese Eagle population. Ultimately, by leveraging advancements in signal processing and deep learning, this research underscores the importance of interdisciplinary collaboration in safeguarding Indonesia's biodiversity and preserving the ecological balance of its natural habitats.

II. Literature Review

In this section discussed about the Javanese eagle, animal sound and the voice of the Javanese eagle's tweet. And a quick overview of literature review on previous research about classification of animal's sounds, MFCC, and CNN deep learning.

A. Javanese Eagle

The Javanese Eagle, scientifically classified as *Spizaetus bartelsi*, represents a distinctive species within the medium-sized bird category. Endemic to the lush landscapes of Java Island, this avian species thrives in the verdant forest that adorn the highlands and mountain slopes. Regrettably, the very existence of the Javanese eagle faces a precarious future, imperiled by the relentless march of time and insidious encroachment of illegal deforestation, which threaten to drive this rare species to the brink of extinction [14]. Historically, the Javanese eagle was a prominent inhabitant of Java Island's forests and mountainous terrains. Yet, in the wake of anthropogenic activities and environmental transformations, the once-thriving population has witnessed a distressing decline. This medium-sized eagle exhibited a body ranging from 60 to 70 cm, measured from the beak to the tip of the tail [15]. The Javanese eagle eats various types of small birds and other poultry, small mammals such as mice, squirrels, rabbits, to medium-sized one such as monkeys. This bird also eats various types of small reptiles such as lizards, monitor lizards, and snakes. This bird lives on the slopes of mountains and hills. Now its existence is only in the rain forest alone. This animal is endemic to the island of Java [16].

B. Animal Sound

Sound is a form of energy that always propagates in all directions in the form of longitudinal waves. Sound can be heard if there is a sound source, medium or intermediary to propagate, as well as an object to listen to / which is used to capture the sound signal. A signal is a variation of variables such as the pressure wave of sound, the color of an image, the depth of a surface, the temperature of a body, the voltage or current of a conductor or biological system, light, radio electromagnetic signals, the price of goods or the volume and weight of an object. It can be said that a signal is a medium to carry information about the past, present and future state of a variable [17].

C. Classification of Sounds

Environmental Sound Classification (ESC) is one of the most challenging tasks in forensic digital signal processing and machine learning. Many methods have been proposed to perform ESC, one of which is self-supervised learning (SSL) for ESC. SSL is a model used to study unsupervised representations by completing pretext tasks and using them to perform downstream task such as classification or regression [18]. This study uses the ESC-10 and DCASE 2019 Task-1(A) datasets. The first dataset used is the ESC-10 containing 400 signals from 10 different types of environmental sounds. 10 types of sounds from the ESC-10 dataset: Dog Barking, Baby Cry, Clock Tick, Fire Cracking, Helicopter, Person Sneezing, Rain, Rooster and Sea Waves. The test signal contains 10 different types of environmental sounds including Airport, Bus, Metro Station, Metro, Park, Public Square, Shopping Mall, Street Pedestrian, Street Traffic and Trams [19]. In this study the model developed uses a spectrogram image as its input, in the early stages of extracting the spectrogram signal. This research discusses the evolution of object detection, highlighting the shift from traditional methods reliant on handcrafted features to deep learning approaches. It emphasizes the advantages of deep learning in learning semantic, high-level features and explores various architectures, training strategies, and optimization functions. The paper provides a comprehensive review of deep learning-based object detection frameworks, covering both generic and specific detection tasks such as salient object detection, face detection, and pedestrian detection. Experimental analyses are conducted to compare methods and suggest future directions for research in object detection and neural network-based learning systems [20]. In this research discusses about an audio extraction technique using MFCC, LPC and DTW and use CNN methods for training and classification process. It develop a hardware module to collect the audio data and sent to the server and used data from online source. The hardware module can function well to classify and send audio signal to the cloud server and store. The audio signal in the cloud server can be reused for the training phase. The highest accuracy obtained reached 91.3% [21].

D. Classification of Animal's Sounds

Research on the classification of animal sounds were carried out by [22, 23]. Reference [22] took the theme of classifying animal sounds using the Convolutional Neural Network method. In this study, the problem of classifying animal sounds using deep learning was investigated and a system based on a convolutional neural network was proposed. The result obtained from this study are unsatisfactory where the highest accuracy is only up to 75% which in the confusion matrix gives the result 4 bird sound are misclassified as cats. While reference [23] took the theme of an IoT-based sound classification system. In this study a well-known feature extraction technique called Mel Frequency Cepstral Coefficient (MFCC) is used to extract features from a given audio clip, send it to the CNN architecture. The result obtained from the research after the dataset test was run on the model, the best accuracy was obtained by AdaDelta, Gradient Descent, and RMSProp optimizer, which was 91.3%, and the worst accuracy was obtained by Momentum optimizer which was 82.6%. Research conducted by [24], with the theme Workflow for automatic identification of animal sounds. In this study, the development and application of a convolutional neural network for the automatic detection of 14 birds and mammals adapted in the forest by classifying spectrogram images generated from short audio clips were explained. The result of this study was stored after Epoch 100 with a training loss of 0.0182, validation loss of 0.0139, training accuracy of 0.9954, and validation accuracy of 0.9969. Research conducted by [25] with the theme of differences between MFCC and IMFCC for the classification of bird sounds. In this study a comparison between MFCC and IMFCC features for automatic bird species recognition systems was carried out with the aim of validating the use of IMFCC features as features that can also be extracted for bird species recognition and the method of bird sound classification system used in this study using Hidden Markov Models (HMM) for data training needs. To compare the efficiency of the features of MFCC and IMFCC with the proposed algorithm using the TAR and TRR performance. Based on the TAR and TRR performance on *Automolus rubiginosus*, *Synallaxis erythrothorax*, *Cardinalis*, *Cercomacra Tyrannina*, and *Myiozetetes Similis* the result of the IMFCC method provide a percentage increase than MFCC. Finally, study conducted by [26], with the theme of a forest fire early warning system with the sound of birds. In this study, the bird data used in the form of recordings of bird sounds from four bird species. The four bird species used in this study were Cipoh, Prenjak, Merbah Cerucuk and Pleci. The result of this study obtained a test accuracy value of 96.45% based on the results of the testing process carried out on the experience of the system program. At this stage it can be concluded that the proposed method is able to classify bird sounds based on the condition of the two birds with an accuracy of 96.45%.

E. Mel Frequency Cepstral Coefficients (MFCC)

MFCC is a method that is quite good and the most widely used in the field of speech recognition. MFCC is a feature extraction that produces in cepstral coefficient parameters. Feature extraction MFCC converts sound waves into several types of parameters, such as the cepstral coefficient, which represent the audio file. In addition, MFCC produces feature vectors that convert voice signals into several vectors for speech feature recognition [27]. MFCC has seven stages, namely pre-emphasis, frame blocking, windowing, Fast Fourier Transform (FFT), Mel Frequency Wrapping (MFW), Discrete Cosine Transform (DCT) and cepstral lifting, which produces parameters like features, namely frames and cepstral coefficient. The final result of MFCC method will improves the quality of the speech recognition, it can be seen using plot from cepstral lifting stage [28].

F. Convolutional Neural Network (CNN) Deep Learning

Convolutional Neural Network (CNN) is one of the deep learning algorithms included in the feed forward class method that is inspired by the visual cortex of the brain. However, to be able to predict well, CNN must be designed with a more complicated architecture. As a result, CNN training is very computationally expensive and has implementation because of its slow speed. CNN has several models in the training process where the method has a different architecture according to the problem. The training model is used in accordance with the state of the object of identification because CNN has several layers implemented at the training stage. The modern CNN discovered by LeChun has seven layer structures (not including the input layer) namely LeNet-5 which has the following structures C1, S2, C3, S4, C5, F6 output [29]. Example of case studies in image recognition on CNN have three stages, namely the input, CNN, and output stages [20]. Input layer is the stage for inserting images into the program and further be processed by changing the image into a binary form so that it can be process at the CNN stage [30]. The CNN algorithm develops multi-layer perceptron (MLP) to process data, one of which is two-dimensional image data, for example images. This CNN algorithm classifies labeled data using the supervised learning method, namely, targeted data and the appropriate variables. Convolutional Neural Network (CNN) has five stages, namely (a) convolution, (b) ReLu layer, (c) max pooling, (d) flattening, and (e) full connection.

III. Methodology

It is not an easy task to extract sound features, recognize them and classify them from various short audio clip. This was due to background noise, very short sound intervals, and fast clip changes. These things interfere with the recognition process carried out by artificial intelligence. Therefore, the recognition of the input voice is very important and affects the result of the voice classification. The system must distinguish the sound that it wants to process and which sound it does not want to process. As a result, the voice data obtained needs to be processed first before entering the voice classification model for processing. The research flow can be seen in Fig. 1.

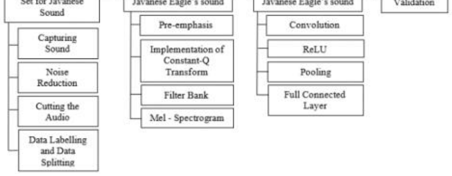

Development Data Set for Javanese Sound
Capturing Sound
Noise Reduction
Cutting the Audio
Data Labelling and Data Splitting
Improved MFCC for Javanese Eagle's sound
Pre-emphasis
Implementation of Constant-Q Transform
Filter Bank
Mel - Spectrogram
Classification of Javanese Eagle's sound
Convolution
ReLU
Pooling
Full Connected Layer
Result and Validation

Fig. 1. Research flows.

A. Develop a Data Set of Sounds of Javanese Eagle

The data used in this study is data in the form of recordings of the sound of birds chirping which is captured by recording on the spot or looking for it in the datasets that are already available. The dataset was divided into two consisting of a true dataset containing the sound of an eagle and a noise dataset. The sounds of the birds used are the sounds of the Javanese eagle so that the sounds of other birds were included in the noise dataset. These two types of data sets were further divided into two, namely the dataset used in the training process and the dataset used in the testing process. The self-collected bird sound clips are short audio clips containing only one tweet. The steps of the Development Data Set for Javanese Sound flow are shown in Fig. 2 below.

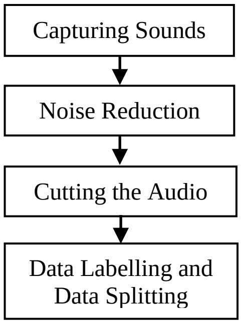


Fig. 2. Development data set for Javanese sound flow.

The preprocessing phase plays a crucial role in the successful identification of Javanese Eagle's primary needs using the hybrid improved Mel-Frequency Cepstral Coefficients (MFCCs) and Deep Convolutional Neural Network (CNN). This phase involves two key steps: Capturing Sounds, noise reduction and cutting audio, and Data Labelling and Data Splitting. The data for Capturing sounds phase are gathered from three specific locations: Taman Safari, PSSEJ and Ragunan Zoo with a total 300 samples for the dataset. After that, to enhancing the signal component the unwanted background noise from the audio signal were attenuate or eliminate using the noise reduction phase [31]. Then the audio data is dissected into individual syllable segment to separate each distinct syllable inside cutting audio phase. After that, the data is assigned with labels and split into three distinct subsets known as training data, validation data and testing data.

B. Develop an Improved Mel Frequency Cepstral Coefficients (MFCC) Technique for Converting the Javanese Eagle Tweet into Spectogram

At this stage, will convert the sound image into the form of a spectrogram using the Improved Mel Frequency Cepstral Coefficients (IMFCC), which will extract the sound features using an artificial intelligence model. The sound spectrogram example is shown in Fig. 3 below.

In order to obtain an effective feature representation for the sound detection of the Javanese eagle, in this study, an improved MFCC-based feature extraction algorithm is proposed. Improved MFCC using Constant-Q (CQT) and Mel Spectrogram. Constant-Q Transform (CQT) is an algorithm that can efficiently compute the Fourier transform. The improved MFCC has two stages before using MFCC itself. The first step is Implementation of Constant-Q Transform (CQT) and the second is Implementation of Mel-Spectrogram. The steps of the improved MFCC flow are shown in Fig. 4 below.

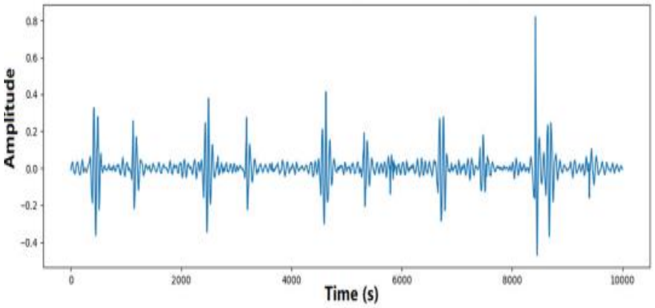


Fig. 3. Sound spectrogram.

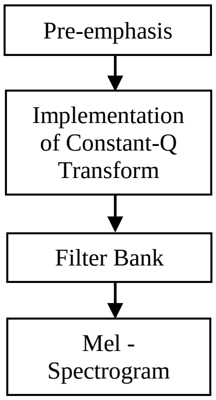


Fig. 4. Improved MFCC.

The audio signal is one-dimensional data, so to convert the audio data it is necessary to convert the audio signal to a log scale time frequency using Constant-Q Transform (CQT). The CQT transformation can be seen in Eq. (1).

$$X[k,n] = \sum_{q=n-\lfloor Nk/2\rfloor}^{n+\lfloor Nk/2\rfloor} x(q)\, a_k^*\left(q - N + \frac{Nk}{2}\right) \tag{1}$$

where, k = 1,2 …, K indexes the catch-frequency coefficient of CQT. Shows a_k^*(n). The basic function of a_k^*(n) is a waveform with complex values. Then in the atomic Eq. (2) the time frequency is defined as follows:

$$a_k(n) = \frac{1}{Nk}\,\omega\left(\frac{1}{Nk}\right) exp\left(-j2\pi\frac{f_k}{f_s}\right) \tag{2}$$

The value fk is the storage centre frequency k, and fs denotes the sampling rate, and w (t) is a continuous window function sampled at the point determined by t. Nk is the length of the window which is inversely proportional to fk in order to achieve the same Q-factor for all k containers. The center frequency fk is defined as Eq. (3) follows:

$$f_k = f_1\, 2^{\frac{k-1}{B}} \tag{3}$$

where, f_1 is the middle frequency of the lowest frequency container, and B is the coefficient to determine the number of containers per octave. In the process, B is an important parameter to make choices when using CQT, because it determines the time-frequency resolution considerations of CQT. The IMFCC consist of four stages, namely: pre-emphasis, implementation of Constant-Q Transform, filter bank and mel- Spectrogram.

C. *CNN for Classification of Eagle's Tweet*

In this study, the classification model used is Convolutional Neural Network (CNN) which consists of three stages, namely: convolution, Rectified Linear Unit (ReLu), and pooling. The CNN training itself will be carried out by repeating the convolution and ReLu stages using the training dataset that has been prepared. CNN itself is used because it has the characteristics of sparse interaction, parameter sharing, and equivalent representation. The steps of the CNN Model are shown in Fig. 5 below.

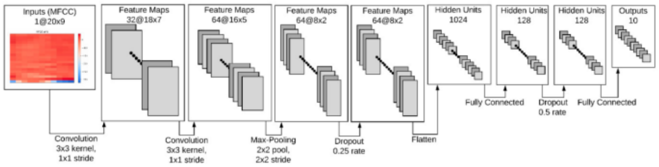


Fig. 5. CNN model.

Introducing a Comparative Analysis: AlexNet and VGGNet for Sound Recognition. Two such seminal architectures, and VGGNet and AlexNet, have etched their names in the annals of deep learning, each characterized by its unique design and contributions. To compare AlexNet and VGGNet effectively, several factors need to be considered, such as model complexity, adaptability to temporal data, and computational efficiency. AlexNet's deep architecture and local response normalization can be modified to accommodate the temporal characteristics of sound, while VGGNet's uniform structure may be better able to capture diverse temporal features. A nuanced approach is necessary to evaluate these architectures, with adaptations and optimizations being crucial to realizing the full potential of both AlexNet and VGGNet in sound classification tasks. AlexNet's architecture is characterized by its depth, large convolutional filters, ReLU activation, and hierarchical feature extraction. The utilization of convolutional layers, max-pooling, and fully connected layers in the architecture of AlexNet facilitated the attainment of cutting-edge performance in picture classification tasks. While, the VGGNet architecture is characterized by its simplicity, regularity, and deep stack of convolutional layers. This design philosophy allows the network to learn hierarchical features of increasing complexity from the input image, making is effective for image classification tasks. The AlexNet CNN and VGGNet Model Architecture are shown in Fig. 6 and Fig. 7 below:

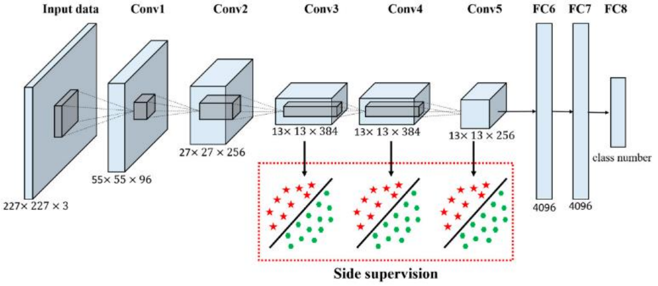


Fig. 6. AlexNet CNN model architecture.

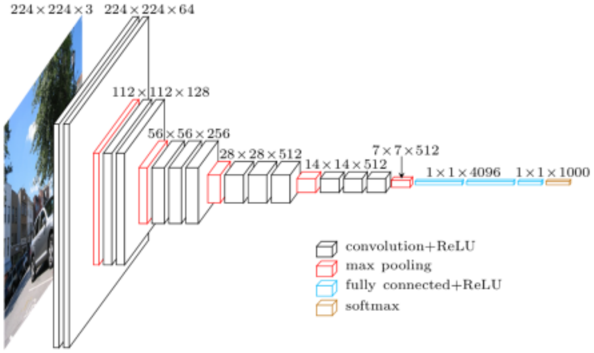


Fig. 7. VGGNet CNN model architecture [32].

1) Convolutional: CNN is a neural network model designed to process data in a grid-like structure. Therefore, the MFCC input in the form of these images will be entered into a matrix that contain the pixel values in the existing image. After that the image map will be multiplied by a matrix that we call the kernel model, for each pixel value of the image matrix. It is this kernel model that the model will study and create. This stage uses mathematical equations such as Eq. (4)

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m,j-n) \quad (4)$$

At the end of the image matrix itself will be filled by an auxiliary variabel with a value of 0. The kernel model will also move by shifting it according to a predefined value, which can call stride. These three parameters are very important at this stage.

2) Rectified Linear Units (ReLu): The result of the image matrix that have been multiplied by this kernel model will be normalized so that negative values in the image matrix must be removed. On CNN, a thresholding process will be carried out, which changes the negative value to zero, using ReLu. ReLu itself has similarities as in equation 3.19 whose activities can be seen in Fig. 10 below.

3) Pooling: After the pixel values have been convoluted and denormalized, the CNN matrix will be reduced in size so that the calculation and classification process become faster and more precise using the pooling method [33]. There are many pooling methods, in this study using the max-pooling method which is very commonly used in CNN and also easy. Basically max-pooling works by grouping the CNN matrix into small matrices and then taking the highest value from the small matrix.

4) Fully connected layer: The CNN matrix values that have gone through the three stages will then proceed to the last stage, namely Fully Connected Layer. At this stage the data obtained from the CNN matrix will be combined and flattened into a one-dimensional layer containing the values from the CNN matrix. This process is often called the flatten process [33]. After completing the flattening stage, the spectrogram image value data that has been generated by CNN will be classified using the SoftMax classifier function.

D. Analysis of Result

To determine the success or failure of this study, it is necessary to Testing data or test data. Tests on learning outcomes are carried out to assess the level of success they have. The success in the test is presented in the form of a percentage, such as the following equation. The results of the test are decisions that were the result from the classification carried out. Testing can be done by using the Correlation coefficient (R), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Square Error (MSE). The equation for the correlation coefficient (R) uses the Eq. (5) as follows:

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})\,(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{j=1}^{N}(y_i - \bar{y})^2}} \quad (5)$$

Furthermore, to calculate the Mean Absolute Error (MAE) can use the Eq. (6) follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \quad (6)$$

Then to calculate the Mean Absolute Percentage Error (MAPE) you can use the Eq. (7) follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|x_i - y_i|}{x^i} \,.\, 100\% \quad (7)$$

And lastly, to calculate the Mean Square Error (MSE) you can use the Eq. (8) follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \quad (8)$$

where, x; y is the target value and predicted value, and N is the number of sample data.

The Confusion Matrix is an indispensable tool for understanding the strengths and weaknesses of a classification model. It allows researchers and practitioners to pinpoint specific areas of improvement, assess the model's robustness, and make informed decisions about model refinement or optimization based on real-world implications. The matrix comprises four essential components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). True Positive (TP) represents instances correctly classified as positive by the model. True Negative (TN) denotes instances accurately identified as harmful. False Positive (FP) signifies instances wrongly classified as positive, and False Negative (FN) includes instances incorrectly identified as harmful.

When the model accurately identifies positive audio samples associated with Javanese eagles, it is denoted as True Positive (TP). On the contrary, True Negative (TN) arises when the model correctly rejects audio samples unrelated to Javanese eagles. False Positive (FP) instances occur when the model incorrectly identifies negative audio samples as positive for Javanese eagles. Finally, False Negative (FN) incidents happen when audio samples relevant to Javanese eagles are incorrectly classified as irrelevant by the model.

Comprehending these concepts aids in evaluating the reliability of the model or system in predicting Javanese eagle sounds. The quantification of TP, TN, FP, and FN counts facilitates the calculation of evaluation metrics such as precision, recall, and F-Score. Precision is the ratio of true positives to the sum of true and false positives, reflecting the accuracy of optimistic predictions. Recall, also known as sensitivity or true positive rate, is the ratio of true positives to the sum of true positives and false negatives, indicating the model's ability to identify all relevant instances. F1-score, a harmonic mean of precision and recall, provides a balanced assessment of the model's overall performance. A confusion matrix is typically presented in a Table I format with rows and columns corresponding to the actual and predicted classes, respectively. Here's a simple representation:

TABLE I. REPRESENTATION OF CONFUSION MATRIX

	Predicted Positive	**Predicted Negative**
Actual Positive	TP	FN
Actual Negative	FP	TN

E. Validation on Expert Verification

Validation through expert verification is a crucial component of this research, ensuring the robustness and reliability of the developed sound classification system for Javanese eagles. Pusat Suaka Satwa Elang Jawa (PSSEJ) serves as the primary domain for this validation process. The expertise of caretakers at PSSEJ plays a pivotal role in assessing the accuracy and effectiveness of the developed system. Their extensive experience caring for Javanese eagles equips them with a nuanced understanding of the eagles' vocal expressions corresponding to distinct needs and providing a real-world evaluation that aligns with the practical aspects of eagle care and conservation efforts. Their validation ensures that the developed system aligns with scientific precision and integrates seamlessly into the context of caretaking at PSSEJ.

IV. RESULT AND DISCUSSION

The outcomes and discussions of the study on sound classification for identifying the primary needs of the Javanese Eagle are presented, employing a hybrid approach of improved Mel-Frequency Cepstral Coefficients (MFCC) and Deep Convolutional Neural Network (DCNN). The section commences with a concise overview of the research objectives and methodology, followed by an elaborate account of the utilized dataset, encompassing the recording process, data pre-processing, and feature extraction.

A. Development of Data Set for Sounds of Javanese Eagle

Data on Javanese eagle sounds were gathered from three separate sites. A bidirectional microphone was used to record audio, which was then saved in uncompressed WAV format with a sampling rate of 44.1 kHz and a resolution of 16 bits. Our machine learning algorithm was trained using the training set, and its performance was assessed using the testing set. Eighty percent of the dataset (240 sound samples) was used for training, and the remaining twenty percent (60 sound samples) was used for testing. The sound clips were pre-processed to remove any background noise, normalize the amplitude, and cut them to a set length of a syllable. The steps in this phase are:

1) *Capturing sound:* The data-gathering process involved recording the sounds produced by Javanese Eagles in their

natural habitat within the park. The recordings were made using a high-quality microphone and a digital audio recorder and conducted during the daytime when the Javanese Eagles were most active and vocal. This study used a bidirectional microphone to record the sounds of Javanese eagles. A bidirectional microphone, also known as a figure-eight microphone, captures sound from two opposing directions while denying sound from other approaches. Using a bidirectional microphone, the sounds of Javanese eagles can be accurately recorded.

2) Noise reduction: The sound data collected has gone through pre-processing once the Javanese eagle's sound was recorded. Pre-processing was the process of cleaning and filtering recorded audio to eliminate distracting elements like background noise. A crucial first step in employing sound classification to determine the main requirements of Javanese Eagles has been data pre-processing. To achieve accurate sound categorization findings, pre-processing has consisted of multiple phases aimed at cleaning and filtering the collected audio data.

This study has made use of spectral subtraction to separate the desired eagle vocalizations from the unwanted background noise present in the audio files. By applying noise reduction to the audio files, undesired background noise has been successfully removed, increasing the sound categorization process' accuracy and precision. Prior to conducting spectral reduction, it has been necessary to apply a High Filter to the sound data. The High filter has served to discriminate between low-frequency sounds and high-frequency sounds.

3) Cutting the audio: Efficient techniques for audio translation were crucial in comprehensively studying and evaluating the noises emitted by Javanese eagles, thereby enhancing our understanding of their behavior and communication. The aim of this method has been to analyze Javanese eagle audio recordings by segmenting them into syllabic units, known as "syllables" in the field of phonetics, with a minimum duration of 0.5 seconds. Additionally, to achieve the best possible outcome, the audio cutting process has utilized the noise-free audio sound.

B. Converting Javanese Eagle Sound into a Spectogram Using Basic Mel Frequency Cepstral Coefficients (MFCC) Technique

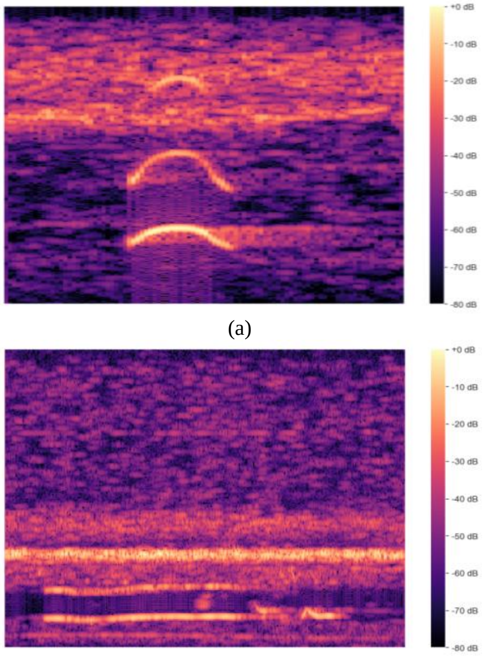
Converting Javanese eagle sounds into spectrograms involves using the basic technique of Mel Frequency Cepstral Coefficients (MFCC) as the primary method. The MFCC method serves as the foundation for generating spectrograms from Javanese eagle sounds, enabling a detailed visual representation of the frequency and energy components of each sound segment.

The MFCC technique involves several crucial steps. First, the sound signal is divided into small time intervals known as frames. Each frame is then analyzed to extract important features encompassing frequency and sound energy information. The next step involves applying Fourier transformation to each frame to convert it from the time domain to the frequency domain. In the MFCC technique, this transformation is typically done using the Short-Time Fourier Transform (STFT). After the transformation, a filter bank is applied to the frequency spectrum to capture more relevant information in the audio spectrum.

1) Pre-emphasis of audio signal: Pre-emphasis is an audio signal processing technique that enhances sound characteristics by emphasizing high frequencies in the signal. This results in a clearer representation of acoustic details and an overall improvement in sound quality.

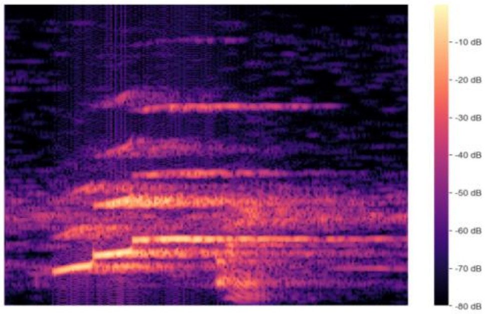
Implementing pre-emphasis on each syllable could enhance comprehension of the acoustic properties of that sound. Additionally, pre-emphasis could mitigate the presence of noise in a speech signal, thereby yielding a more pristine rendition of the sound. The pre-emphasis was implemented on sound signals at the syllable level.

2) Implementation of Short-Time Fourier Transform (STFT): STFT is used to analyze how the frequency of an audio signal changes over time. This technique divides the audio signal into small segments called frames and then performs Fourier transformations on each of these frames. The STFT process enables us to observe how the frequency in an audio signal changes over time, thereby generating a spectral representation of the signal. STFT is employed after obtaining the audio signal that has undergone pre-emphasis. The implementation of STFT in this study, the configuration used includes a NFFT of 512, a window length of 256, a hop length of 128, and the use of a 'hamming' window. The effect of applying the Short-Time Fourier Transform (STFT) on syllables explained in Fig. 8. Fig. 8(a), (b), and (c) depict the STFT representations.



(a)

(b)



(c)

Fig. 8. (a) STFT on normal tweets, (b) STFT on looking for food tweets, (c) STFT on looking for partner tweets.

3) Filter bank implementation for STFT representation: This Filter bank operates by segregating the frequency signal into smaller sub-bands. By applying Filter bank to STFT, frequency information from the audio signal can be more effectively separated, allowing for a more detailed analysis of each frequency sub-band. Each filter within the Filter bank responds to specific frequency ranges. The fusion of STFT and Filter bank has enabled the creation of Mel Spectrogram, facilitating the analysis of Javanese eagle vocalizations within a frequency range similar to human auditory perception and sound processing. This aids in understanding significant changes in the acoustic characteristics of Javanese eagle sound. The resulting Mel Spectrogram serves as a visualization of frequency representation in the form of a spectrogram derived from employing Filter bank techniques on the STFT output.

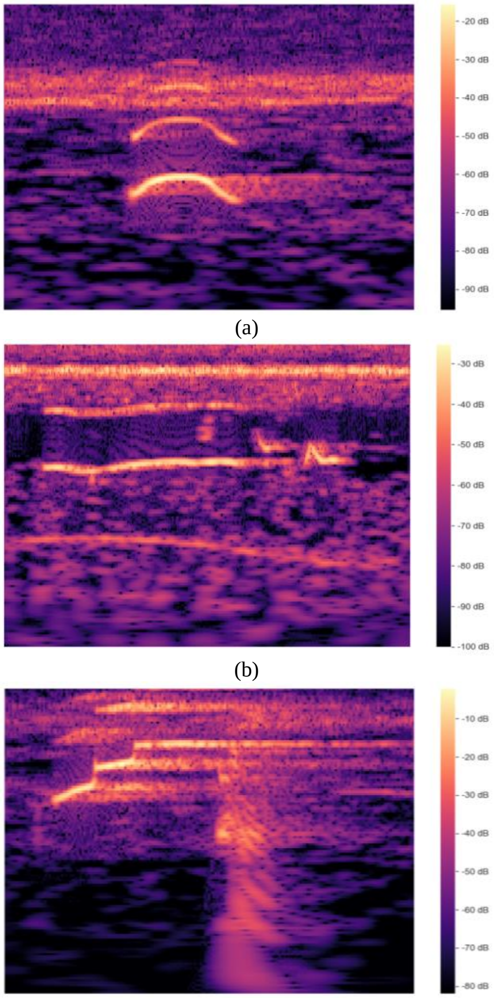
4) Converting a normalized Mel Spectrogram to an image representing the audio: The representing Javanese eagle sound were transformed into a visual image from a standard Mel Spectrogram. The aim is to illustrate audio data in an easily comprehensible visual format, aiding in a simpler understanding of the vocal attributes of the Javanese eagle. The initial step in this study involves normalizing the Mel Spectrogram. Normalization is a crucial procedure to convert spectral data into a standardized format suitable for analysis. The normalization of the Mel spectrogram function balanced the spectrum and increased the Signal-to-Noise Ratio (SNR).

C. Converting Javanese Eagle Sound into a Spectrogram Using Improved Mel Frequncy Cepstral Coefficients (IMFCC) Technique

The objective of this study was to provide a novel method for assessing the noises produced by Javanese eagles by transforming them into a visually informative representation known as a spectrogram. The Improved Mel Frequency Cepstral Coefficient (Improved MFCC) technique was employed, involving the substitution of the Short-Time Fourier Transform (STFT) with the Constant-Q Transform (CQT). This research utilizing Javanese eagle vocalizations that had been divided into syllabic segments. Segmentation facilitated the detection of variations in the vocalization of the Javanese eagle, such as alterations in pitch or rhythm that might have been present within each syllable.

1) Pre-emphasis of audio signal: Applying pre-emphasis to each syllabic segment holds the potential to enhance understanding of the acoustic characteristics of that sound. This process aids in distinguishing sounds with high intensity at high frequencies from those with a more balanced frequency range. Additionally, pre-emphasis can reduce noise in speech signals, resulting in a cleaner and clearer representation of the sound.

2) Implementation of Constant-Q transform: The CQT setup we used to comprise multiple essential settings. The hop length was configured at 128, and the transformation process employed 'hamming' windows. By utilizing CQT with this particular configuration, it was expected that a more accurate and informative spectral representation of the Javanese eagle's vocalizations could be obtained at the syllable level. The effects of applying the Constant-Q Transform (CQT) on syllables that had undergone pre-emphasis in the preceding sub-chapter are depicted in Fig. 9 below. Fig. 9(a), (b), and (c) depicted a CQT representation, which provided information about energy levels across different frequencies during a certain period of time.



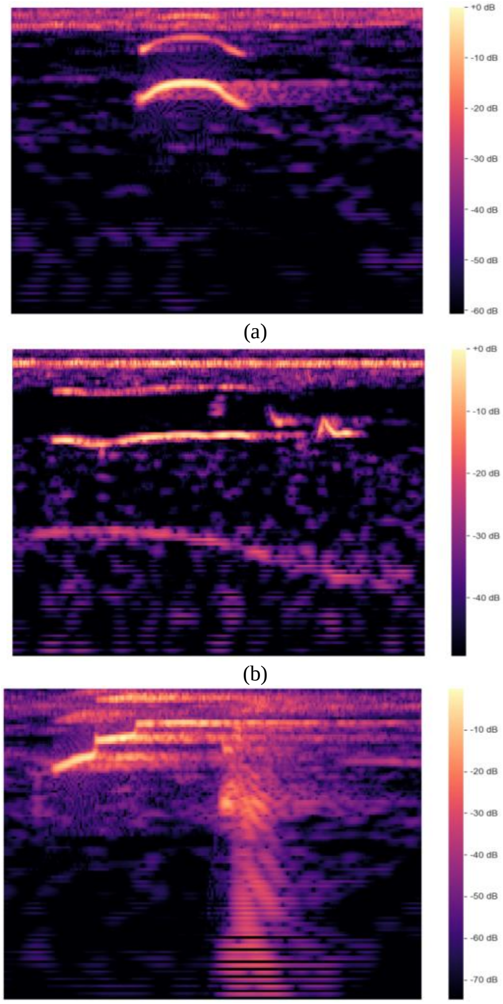
(a)

(b)

(c)

Fig. 9. (a) CQT on normal tweets, (b) CQT on looking for food tweets, (c) CQT on looking for partner tweets.

3) Filter bank implementation for CQT representation: This study involved the creation of a novel technique for evaluating the sounds of Javanese eagles. It achieved this by combining Filter bank with the Constant-Q Transform (CQT) output to generate a more detailed spectral representation called the Mel Spectrogram. The fusion of Constant-Q Transform (CQT) and Filter bank has enabled the generation of a Mel Spectrogram, which facilitated the examination of the vocalizations of the Javanese eagle in a frequency domain that closely aligns with human auditory perception and sound processing. This has aided in comprehending significant alterations in the acoustic properties of sound. The outcome of applying Filter bank to the CQT output has yielded a Mel Spectrogram, as seen in Fig. 10 below. Fig. 10(a), (b), and (c) depicted a Mel Spectogram representation.



(a)

(b)

(c)

Fig. 10. (a) Normal tweets, (b) Looking for food tweets, (c) Looking for partner tweets Mel spectrogram.

4) Converting a normalized Mel Spectrogram to an image representing the audio: The representing Javanese eagle sound were transformed into a visual image. The first phase in this investigation involved normalizing the Mel Spectrogram. Normalization was a crucial procedure for transforming spectral data into a standardized format suitable for analysis using mean normalization approach to normalize the data, resulting in a spectral average of zero and decreased data variability. The normalization of the Mel spectrogram function balanced the spectrum and increased the Signal-to-Noise Ratio (SNR).

D. Convolutional Neural Network (CNN) Deep Learning for Classifying the Tweets of Javanese Eagle Spectrogram

Convolutional Neural Networks (CNNs) have been a potent category of deep learning models that have demonstrated remarkable efficiency in many picture and signal processing applications, including the classification of spectrograms, such as those depicting the tweets of the Javanese Eagle. Spectrograms are graphical depictions of audio signals, illustrating the variations in frequency components as they evolve over time. By utilizing a Convolutional Neural Network (CNN) and providing it with a dataset of categorized Javanese Eagle tweets, the network has acquired the ability to identify and differentiate unique auditory patterns linked to other categories, such as diverse calls or behaviors exhibited by the eagles.

1) Data Validation and Image Pre-processing: Data validation was crucial in the context of training Convolutional Neural Networks (CNN) on Javanese Eagle sound spectrograms to ensure the dataset's trustworthiness. Spectrogram picture data was considered valid only if it had a file extension of png, jpg, or bmp. This approach guaranteed that only image data adhering to the required format was used for training, preventing any compatibility problems that might have arisen and led to errors during the preprocessing and model training stages.

After completing the data validation stage, the subsequent step involved image preprocessing. This procedure involved modifying the dimensions of the spectrogram image to fulfill the specifications of the CNN model. the spectrogram image underwent a conversion process to either a size of 227 x 227 or 224 x 224. Therefore, the picture preprocessing procedure readied the dataset in a suitable format and ensured the data was prepared for utilization in CNN training for the interpretation of Javanese Eagle sound spectrograms.

2) Data splitting and data labelling: Data labeling and data splitting were two crucial stages in data preprocessing for training and assessing Convolutional Neural Network (CNN) models. Data labeling involved assigning a specific label or category to each individual data instance inside a dataset. Labels were crucial for CNN models to acquire knowledge and comprehend the correlation between characteristics (attributes) and intended outputs. In an image classification task, each image had to be assigned a label that indicated the object or category seen in the image.

Data splitting entailed the partitioning of a dataset into three distinct subsets, commonly known as training data, validation data, and testing data. The objective was to partition a subset of data for the purpose of training a Convolutional Neural Network (CNN) model, referred to as the training data.

Subsequently, data that had not been previously encountered during training was employed to evaluate the CNN model's ability to generate precise predictions, known as the test data. Validation data was employed throughout the training process to oversee and enhance the model. The data splitting are shown in Table II below.

TABLE II. DATA SPLITTING

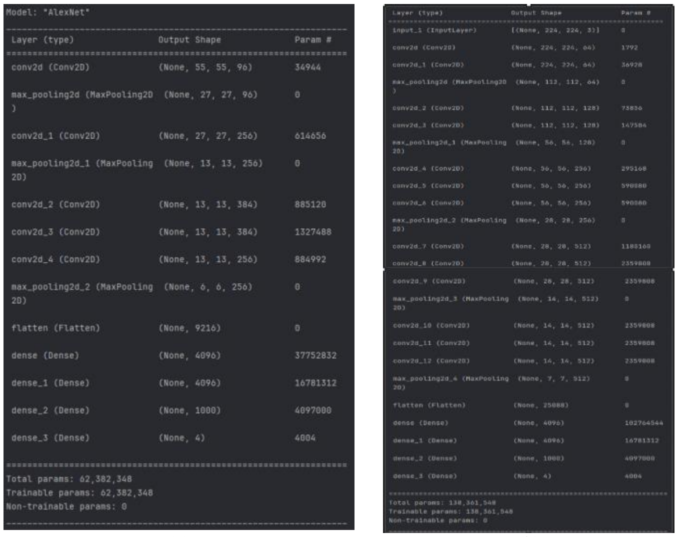
Experiment	Data	Training	Validation	Testing
Experiment I	900	630 (70%)	90 (10%)	180 (20%)
Experiment II	900	630 (70%)	180 (20%)	90 (10%)
Experiment III	900	720 (80%)	90 (10%)	90 (10%)

3) CNN Architecture Model: The Convolutional Neural Network (CNN) architecture has served as the fundamental framework in image processing and has consisted of multiple layers that collaborated to achieve a profound comprehension of picture data. The method commences with convolution layers, where tiny filters or kernels are employed to extract distinctive features like edges, textures, and patterns from the image. The outcome is a feature map that accentuates significant details within the image.

Max Pooling layers have typically succeeded convolution layers, serving to reduce data dimensionality and computational complexity by selecting the highest value within an overlapping region. Subsequently, a Flatten layer is employed to transform the three-dimensional feature map into a singular, one-dimensional vector. A Dense layer is a type of neural network layer characterized by having every neuron connected to every neuron from the previous layer. This means that there is a full and direct connection between all neurons in the layer and the neurons in the previous layer. The ReLU (Rectified Linear Unit) activation function is applied to each neuron in the Dense and convolution layers to introduce non-linearity to the model, aiding in acquiring more intricate features. The Softmax activation function computes the probabilities for each distinct class, and the class with the highest probability is selected as the final prediction of the model.

Apart from that, two architectures have been employed, namely Alex Net and VGGNet-16. The architectures were used in the training, testing and evaluation process for experiments 1, 2, and 3 that have been carried out. Model summary of Alex Net and VGGNet-16 were displayed in Fig. 11.

4) Training and testing CNN model: Assessing the performance of a Convolutional Neural Network (CNN) model during training is crucial. This involves tracking loss function values and accuracy to gauge the model's success in categorizing the training data. Choosing the appropriate number of epochs is important, with 25 epochs being ideal to ensure the model converges well. Evaluating the model's performance is done through experiments on the dataset, with results providing valuable insights into the impact of validation and testing dataset sizes and the proportion of training data. After training, the model is tested on never-before-seen testing data to evaluate its ability to generalize learned information. Evaluation metrics such as accuracy, precision, recall, F1-score, Confusion Matrix, and AUC-ROC curve offer valuable insights into the model's effectiveness in classifying previously unseen new data.



```
Model: "AlexNet"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 55, 55, 96)        34944

 max_pooling2d (MaxPooling2D  (None, 27, 27, 96)       0
 )

 conv2d_1 (Conv2D)           (None, 27, 27, 256)       614656

 max_pooling2d_1 (MaxPooling  (None, 13, 13, 256)      0
 2D)

 conv2d_2 (Conv2D)           (None, 13, 13, 384)       885120

 conv2d_3 (Conv2D)           (None, 13, 13, 384)       1327488

 conv2d_4 (Conv2D)           (None, 13, 13, 256)       884992

 max_pooling2d_2 (MaxPooling  (None, 6, 6, 256)        0
 2D)

 flatten (Flatten)           (None, 9216)              0

 dense (Dense)               (None, 4096)              37752832

 dense_1 (Dense)             (None, 4096)              16781312

 dense_2 (Dense)             (None, 1000)              4097000

 dense_3 (Dense)             (None, 4)                 4004

=================================================================
Total params: 62,382,348
Trainable params: 62,382,348
Non-trainable params: 0
_________________________________________________________________
```

(a)

```
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 224, 224, 3)]     0

 conv2d (Conv2D)             (None, 224, 224, 64)      1792

 conv2d_1 (Conv2D)           (None, 224, 224, 64)      36928

 max_pooling2d (MaxPooling2D  (None, 112, 112, 64)     0
 )

 conv2d_2 (Conv2D)           (None, 112, 112, 128)     73856

 conv2d_3 (Conv2D)           (None, 112, 112, 128)     147584

 max_pooling2d_1 (MaxPooling  (None, 56, 56, 128)      0
 2D)

 conv2d_4 (Conv2D)           (None, 56, 56, 256)       295168

 conv2d_5 (Conv2D)           (None, 56, 56, 256)       590080

 conv2d_6 (Conv2D)           (None, 56, 56, 256)       590080

 max_pooling2d_2 (MaxPooling  (None, 28, 28, 256)      0
 2D)

 conv2d_7 (Conv2D)           (None, 28, 28, 512)       1180160

 conv2d_8 (Conv2D)           (None, 28, 28, 512)       2359808
 conv2d_9 (Conv2D)           (None, 28, 28, 512)       2359808

 max_pooling2d_3 (MaxPooling  (None, 14, 14, 512)      0
 2D)

 conv2d_10 (Conv2D)          (None, 14, 14, 512)       2359808

 conv2d_11 (Conv2D)          (None, 14, 14, 512)       2359808

 conv2d_12 (Conv2D)          (None, 14, 14, 512)       2359808

 max_pooling2d_4 (MaxPooling  (None, 7, 7, 512)        0
 2D)

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 4096)              102764544

 dense_1 (Dense)             (None, 4096)              16781312

 dense_2 (Dense)             (None, 1000)              4097000

 dense_3 (Dense)             (None, 4)                 4004

=================================================================
Total params: 138,361,548
Trainable params: 138,361,548
Non-trainable params: 0
_________________________________________________________________
```

(b)

Fig. 11. Model summary of (a) Alex net, (b) VGGNet-16.

Experiment 1: The trained MFCC with AlexNet model achieved 97% accuracy in identifying Javanese Eagle's sound patterns. However, the testing showed a slightly lower accuracy rate of 95% with some identification failures in specific categories, indicating the need for further improvement.

Experiment 2: The trained MFCC with VGGNet Model showed stable accuracy despite a significant increase in loss. Testing showed an accuracy rate of 94% with some identification failures in specific categories. The early stopping method was effective in optimizing the training process.

Experiment 3: The trained MFCC with AlexNet Model achieved 97% accuracy in identifying Javanese Eagle's sound patterns. However, the testing showed a slightly lower accuracy rate of 93% with some identification failures in specific categories, indicating the need for further improvement.

Experiment 4: The trained MFCC with VGGNet model on a 70:20:10 dataset split achieved 97% accuracy during training. However, there was a significant increase in loss values during epochs 15-20. The early stopping method was implemented at epoch 20 and proved successful. The model's ability to classify spectrogram images remained highly reliable during testing.

Experiment 5: The trained MFCC with AlexNet model achieved 98% accuracy during training, showcasing exceptional ability to capture the patterns and characteristics within the spectrogram data. The model's performance during testing remained highly accurate.

Experiment 6: The trained MFCC with VGGNet model achieved 98% accuracy during training, showcasing exceptional ability to capture the patterns and characteristics within the spectrogram data. The model's performance during testing remained highly accurate.

Experiment 7: A CNN with AlexNet architecture was trained to learn the IMFCC spectrogram of Javanese Eagles. The model achieved an accuracy rate of 99% during training. In testing, it achieved an accuracy rate of 98% with some identification failures.

Experiment 8: A CNN with VGGNet architecture was trained to learn the IMFCC spectrogram of Javanese Eagles. The model achieved an accuracy rate of 97% during training. In testing, it achieved an accuracy rate of 97% with some identification failures.

Experiment 9: A CNN with AlexNet architecture was trained to learn the IMFCC spectrogram of Javanese Eagles. The model achieved an accuracy rate of 97% during training. In testing, it achieved an accuracy rate of 97% with some identification failures.

Experiment 10: The results of training a CNN with VGGNet architecture to learn the IMFCC spectrogram of Javanese Eagles are not provided in the given text.

Experiment 11: The IMFCC and AlexNet models were trained and tested for the 80:10:10 dataset. The AlexNet architecture recognized and learned the sound patterns of Javanese Eagles with high precision, achieving an accuracy rate of 98% during training. Testing involved classification analysis, Confusion Matrix, and ROC Curve, with an overall accuracy rate of 97%.

Experiment 12: The IMFCC and VGGNet models were trained and tested for the same dataset. The VGGNet architecture achieved a peak accuracy rate of 100% during training and an accuracy rate of 99% during testing. The ROC Curve showed an area under the curve of 0.996 for the 'Normal' category, 1.000 for 'Looking For Partner', and 0.996 for 'Looking For Food'.

Improved Mel Frequency Cepstral Coefficient (IMFCC). The CQT approach in IMFCC was found to be more precise that the Short-Time Fourier Transform in MFCC. In experiment 12, the CNN model based on the VGGNet-16 architecture achieved 99% accuracy. The resulting AUC value shows an Average Recall of 0.89, an Average Specificity of 0.965, and an Area under Curve (AUC) value of 0.93. The MAPE value for the LookingForFood class is 0.006; for the LookingForPartner class, it's 0.315; and for the Normal class, it's 0.045. The average MAPE value can be calculated by adding the MAPE values for each class and dividing the result by the number of classes. In this case, the average MAPE value is (0.006 + 0.315 + 0.454) / 3 = 0.141. Precision for LookingForFood was 0.93, for LookingForPartner it was 1.00, and for Normal, it was 0.95. The F-Score values for the classes were 0.96 for LookingForFood, 0.81 for LookingForPartner, and 0.97 for Normal. These values calculate the average F-Score as (0.96 + 0.81 + 0.97) / 3 = 0.91. This results show that the purposed method is suitable for detecting real-time Javan Hawk-Eagle sounds.

5) CNN model validation: The evaluation process begins by considering the complexity of analyzing real-time sound recordings of the Javan hawk-eagle. The CNN model, utilizing the VGGNet-16 architecture, undergoes rigorous testing, analyzing the intricate vocalizations of these birds within audio frames. The raw dataset, consisting of the model's predictions, acts as a preliminary insight into the model's performance. Instances where the Javan hawk-eagle sounds are correctly identified with confidence reflect the model's accuracy. The VGGNet-16 architecture-based CNN model achieved 99% accuracy in experiment 12, making it suitable for detecting real-time Javan hawk-eagle sounds.

Metrics like the Area under Curve (AUC), Mean Absolute Percentage Error (MAPE), and F-Score are pivotal in this evaluation to measure the model’s performance. The evaluation csv file contains authentic sound recordings, labels, and tweet counts directly obtained from the Javanese Eagle conservation site. It provides a deep understanding of the Javan hawk-eagle sound detection balance between precision and recall, aiding in refining and enhancing the accuracy and reliability of the model for better practical applications in sound detection in natural environments.

The prediction results were processed to compare the predicted data with the actual data, which can be observed in the actual and predicted tweet sounds image. The Confusion Matrix generated from the prediction outcomes for each audio file in Evaluation.csv provides a detailed breakdown of the model's performance in classifying different sound categories from the audio files in the evaluation dataset. Lastly, the metrics TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) derived from the Confusion Matrix present a detailed account of the model's performance in accurately identifying each class and its corresponding errors or correct identifications.

The Area under Curve (AUC) is a performance metric used to measure the reliability of classification models in distinguishing between different classes. AUC measures how well the model recognizes instances of a class and separates that class from others. The average Recall and Specificity values for each class are then computed to calculate the AUC, which ranges from 0 to 1. A high AUC value signifies that the model exhibits proficiency in distinguishing between behaviors.

The Mean Absolute Percentage Error (MAPE) is a metric used to measure the relative error in a model's predictions. It is crucial in evaluating the accuracy of the model's prediction for each behavior class of Javanese eagles. MAPE is computed by averaging the absolute percentage errors between the actual and predicted values. Lower MAPE values indicate the model's ability to accurately predict eagle behavior, while higher values signify a greater level of inaccuracy.

The F-Score is an essential metric for evaluating the performance of classification models in identifying Javan Hawk-Eagle behaviors. It combines Precision and Recall to provide an overview of how well the model can differentiate between LookingForFood, LookingForPartner, and Normal behaviors based on the observed sounds. Precision measures the accuracy of the model's predictions for a specific class, while Recall evaluates how well the model can identify all instances of that class.

V. Conclusion and Future Works

In conclusion, the research presented a novel approach, combining Improved Mel Frequency Cepstral Coefficients (IMFCC) with Deep Convolutional Neural Networks (CNN), to decode the intricate vocalizations of the Javanese Eagle. The research aimed to decode the Javanese Eagle's vocalizations by combining Improved Mel Frequency Cepstral Coefficients (MFCC) with Deep Convolutional Neural Networks (CNN), promising enhanced comprehension and species conservation. Using IMFCC, experiment 12 achieved 99% accuracy with VGGNet-16 architecture, showing significant promise in real-time sound detection. The method achieved high accuracy rates, demonstrating its suitability for real-time sound detection. With an Average Recall of 0.89, an Average Specificity of 0.965, and an AUC value of 0.93, the study's findings underscore the effectiveness of the proposed technique in understanding and classifying Javanese Eagle sounds.

Moving forward, future research avenues include exploring alternative machine learning models such as Recurrent Neural Networks (RNNs) and Convolutional Recurrent Neural Networks (CRNNs) to improve temporal analysis. Additionally, investigating advanced feature extraction techniques beyond IMFCCs, like Hybrid Cepstrum Analysis (HCA) or Mel-Spectrograms, could provide deeper insights. Further exploration of evaluation metrics focusing on temporal accuracy and ethical considerations surrounding model deployment in natural environments will enhance the robustness and applicability of sound detection and recognition systems.

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Ethnicity Classification Based on Facial Images using Deep Learning Approach

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***Abstract*—Race and ethnicity are terminologies used to describe and categorize humans into groups based on biological and sociological criteria. One of these criteria is the physical appearance such as facial traits which are explicitly represented by a person’s facial structure. The field of computer science has mostly been concerned with the automatic detection of human ethnicity using computer vision-based techniques, where it can be challenging due to the ambiguity and complexity on how an ethnic class can be implicitly inferred from the facial traits in terms of quantitative and conceptual models. The current techniques for ethnicity recognition in the field of computer vision are based on encoded facial feature descriptors or Convolutional Neural Network (CNN) based feature extractors. However, deep learning techniques developed for image-based classification can provide a better end to end solution for ethnicity recognition. This paper is a first attempt to utilize a deep learning-based technique called vision transformer to recognize the ethnicity of a person using real world facial images. The implementation of Multi-Axis Vision Transformer achieves 77.2% classification accuracy for the ethnic groups of Asian, Black, Indian, Latino Hispanic, Middle Eastern, and White.**

Keywords—Vision transformer; deep learning; ethnicity; race; classification; recognition

I. Introduction

The terms race and ethnicity are often used interchangeably which leads to misconception in some circumstances. The word race is used to categorize humans into groups biologically based on physical appearance traits inherited from the ancestors [1], whereas the term ethnicity is used to categorize humans into groups ethnographically based on geographic regions, language, cultural tradition, and shared ancestry which could refer to the similar physical appearance traits inherited but not inclusively [2].

Racial categories were first proposed in 1779s by Johann Friedrich Blumenbach, these categories were Ethiopian-black race, Caucasian-white race, Mongolian-yellow race, American-red race, and Malayan-brown race [3]. A commonly adopted racial categorization is proposed by the U.S. Census Bureau where they categorize race into White, Black or African American, American Indian or Alaska Native, Asian, Native Hawaiian and Pacific Islander [4]. The White race represents the ethnic groups originating in Europe, the Middle East, and North Africa. The Black race represents the ethnic groups originating in South Africa, Nigeria, Ghana, Kenya, etc. The American Indian or Alaska Native race represents the ethnic groups originating in North and South America also including Central America. The Asian race represents the ethnic groups originating in East or Southeast Asia, and the Indian subcontinent. The Native Hawaiian and Pacific Islander race represent the ethnic groups originating in Hawaii, Guam, Samoa, and other Pacific Islands [5].

The human face conveys a set of semantic traits; these traits can be used to conclude several attributes for a person such as identity, gender, age, race or ethnicity, and expressions [6]. The human face is the area from the upper edge of the forehead to the chin and from the left ear to the right ear. The structure of the facial area is represented in three main regions which are superior, middle, and inferior. The superior region describes the shape of the forehead, eyebrows, and eyes. The middle region describes the shape of the nose, cheeks, and ears. The inferior region describes the shape of the lips, chin, and jawline [7]. Thereby, the shape of the facial structure provides discriminant appearance traits from one person to another's. In facial recognition systems based on computer vision techniques the shape of the facial structure is referred to as facial features. The complexity of facial recognition systems lies in the process of transformation from visual facial features to a quantitative representation of the data.

Majority of the proposed methods are based on facial features descriptors where pre-defined procedures are performed to capture and analyze facial images to construct a geometry map of facial traits such as the shapes of the mouth, nose, eyes and facial landmarks or image texture such as skin color. Then the extracted features are encoded into a feature vector to be used in a classifier [8]. However, recent methods are mainly based on the automation of feature extraction using deep learning such as convolutional neural network (CNN) models, which have achieved better accuracy and generalization results when trained with a sufficient amount of representative data [8].

The lack of exploitation of deep learning techniques other than CNN motivated the study of deep learning techniques that can model the facial features for ethnicity recognition. This paper employs the deep learning model Multi-axis Vision Transformer (MaxViT) proposed by Google research team [9] for the purpose of image-based classification. The objective is to test the capability of MaxViT to recognize cognate facial features that implicitly represent the discriminative appearance traits which distinguish one ethnic group from other using facial images. The proposed model is trained on a database created by merging three different ethnicity datasets namely FairFace [10], UTKFace [11], and Arab face dataset [12]. The main contribution is that the proposed model achieves better generalization capabilities compared to other models with an accuracy of 77.2% for classifying six ethnic groups i.e., Asian, Black, Indian, Latino Hispanic, Middle Eastern, and White. The utilization of deep learning techniques such as MaxViT would significantly improve the current state of the art for ethnicity recognition with implication for various fields such as human computer interaction and video surveillance.

II. Related Work

A. Databases

One of the crucial factors for the advancement in the scope of race or ethnicity recognition in computer vision is the availability of a large and diverse dataset that provides reliable annotated facial images based on racial or ethnic categories. However, the research area of ethnicity recognition is still lacking in this factor, as no dataset that represents all the racial or ethnic groups is available. One of the most recently proposed datasets is called FairFace [10] consisting of 97,698 images for seven ethnic groups (Black, East Asian, Indian, Latino Hispanic, Middle Eastern, Southeast Asian, and White) labeled by age, gender, and ethnicity. Another dataset proposed in the field of ethnicity recognition by Zhifei Zhang et al. [11] called the UTKFace dataset consists of 20,000 images for five ethnic groups (Asian, Black, Indian, White, Others) labeled by age, gender, and ethnicity. The dataset proposed by Ziwei Liu et al. [13] called Labelled Faces in the Wild (LFW) consists of 13,233 images for three ethnic groups (Asian, Black, White) labeled by gender, and ethnicity. MORPH dataset proposed by Karl Ricanek et al. [14] consists of 55,134 images for five ethnic groups (African, European, Asian, Hispanic, Others). BUPT-BALANCEDFACE dataset proposed by Mei Wang et al. [15] consists of more than one million images for four ethnic groups (Asian, African, Indian, and Caucasian). BUPT-GLOBALFACE dataset proposed by Mei Wang et al. [16] consists of two million images for four ethnic groups (Asian, African, Indian, and Caucasian). Mivia Ethnicity Recognition (VMER) dataset composed from VGG-Face2 dataset [8,17] and consisting of more than three million images for the ethnic groups (African American, East Asian, Caucasian Latin, and Asian Indian). There are many other facial datasets such as Diversity in Faces (Dif) [18], IMDB-WIKI dataset [19], and Cross-Age Reference Coding (CARC) dataset [20], these datasets are not optimally oriented toward ethnicity recognition.

B. Conventional Feature Extraction

This section summarizes the methods that have been commonly used for facial features extraction using computer-vision techniques for race or ethnicity recognition.

A study conducted by L. Farkas [21] which is based on the relations between well-defined facial landmarks in terms of the Euclidean distance between two points, the angle formed by a point and two other points, and the perpendicular distance from a point to the straight line between two other points. This study shows that these relations can be used to distinguish the differences in facial features of different ethnic groups. Therefore, the use of geometric facial features to classify ethnic groups is applicable. On the other hand, Xiaoguang et al. [22] used appearance-based approaches that extract facial features based on the pixel intensity values in a black-and-white image of the face. This method achieved high accuracy when implemented to classify between two ethnic groups Non-Asian, and Asian, however, this method may be insufficient to classify between more specific ethnic groups because it can vary significantly based on images quality factors such as resolution, viewing angles, and illumination. Another appearance-based approach proposed by G. Zhang et al. [23] which is based on the invariant of monotonic transformation in the grayscale images using Local Binary Pattern histograms to describe the texture and shape variations. S. Hosoi et al. [24] extracted ethnic facial features using Gabor Wavelet Transformation besides Retina sampling. Their proposed method achieved a high accuracy relative to the number of ethnic groups concluded in the experiment. An approach proposed by N. Narang et al. [25] to extract facial features from images by locating eye centers using manual annotation and affine transformation to construct a geometric representation of face images. Kazimov T. et al. [26] proposed a method to define ethnic features based on the Euclidean distance between 30 geometric landmarks. H. Ding et al. [27] proposed an approach based on 3D face models where ethnic features are extended using Oriented Gradient Maps. M. A. Uddin et al. [28] proposed an integrated approach to classify the ethnicity of Caucasian, African, and Asian based on texture and shape features using a histogram of oriented gradients and Gabor filter to extract features from a grayscale image, and then combining both feature vectors into one.

C. Deep Learning-based Feature Extraction

This section summarizes the deep learning approaches that have been proposed previously for feature extraction for ethnicity recognition.

Marwa Obayya et al. [29] used a fusion of three pre-trained CNN models as feature extractors, namely VGG16, Inception v3, and capsule networks. And a bidirectional long short-term memory model as a classifier, the model is trained using VMER dataset and achieves an accuracy of 70% for classifying four ethnic groups of African American, East Asian, Caucasian Latin, and Asian Indian. Gurram Sunitha, K. et al. [30] used a pre-trained Xception CNN model as a feature extractor and kernel extreme learning machine model is used as classifier. The model is trained using the BUPT-GLOBALFACE dataset and achieves an accuracy of 97% for classifying four ethnic groups of Asian, African, Caucasians, and Indian. Norah A. Al-Humaidan et al. [12] used a pre-trained ResNet50 CNN model as a feature extractor and a fully connected layer for classification. The model is trained on a sub-ethnic group of Arabs dataset consisting of 5,598 images of Gulf Cooperation Council (GCC) countries people, 1,665 images of Levant people, and 1,555 images of Egyptian people. The model achieved 76% classification accuracy. Heng Zhao et al. [31] proposed ethnicity recognition framework by utilizing a CNN model, Content-Based Image Retrieval model (CBIR), and Support Vector Machines (SVM) classifier. A VGG-16 CNN model is used for feature extraction and a Bag-of-Words model is used as CBIR, a combination of CNN feature and ranking feature are used to train SVM model for classification. The model is trained using a dataset consisting of 1,000 images of Bangladeshi people, 1,520 images of Chinese people, and 1,078 images of Indian people. The model achieved 95%

classification accuracy. Hu Han et al. [32] used a modified AlexNet CNN model with batch normalization layers for feature extraction and two fully connected layers for classification. The model is trained on MORPH-II dataset achieving 96% classifying accuracy for three ethnic groups of Black, White, and Other. Anwar Inzamam et al. [33] used a pre-trained VGG-Face CNN model for feature extraction and a SVM model as a classifier. The model is trained on ten different databases, using ten-fold cross-validation where nine databases are used for training and one for testing. The model achieved 98% average classification accuracy over all databases for three ethnic groups of Asian, White, and Black. Amr Ahmed et al. [34] used a Feed-Forward based CNN model and max pooling layer for classification. The model is trained using Face Recognition Grand Challenge dataset achieving 93% classifying accuracy for three ethnic groups of Asian, White, and Other.

A summary of related work based on deep learning approach is shown in Table I, describing the model used, the number of ethnicity groups classified by the model and accuracy achieved by the model compared to the proposed model.

TABLE I. A SUMMARY OF RELATED WORK BASED ON DEEP LEARNING APPROACH

Author	Method	Ethnicity groups	Accuracy
Marwa Obayya et al. [29]	Fusion of VGG16, Inception v3, and capsule network CNN models	African American, East Asian, Caucasian Latin, and Asian Indian	70%
Gurram Sunitha, K. et al. [30]	Xception CNN model	Asian, African, Caucasians, and Indian	97%
Norah A. Al-Humaidan et al. [12]	ResNet50 CNN model	GCC people, Levant, and Egyptian	76%
Heng Zhao et al. [31]	VGG-16 CNN model	Bangladeshi, Chinese, and Indian	95%
Hu Han et al. [32]	AlexNet CNN model	Black, White, and Other	96%
Anwar Inzamam et al. [33]	VGG-Face CNN model	Asian, White, and Black	98%
Ahmed et al. [34]	Feed-Forward based CNN model	Asian, White, and Other	93%
Proposed model	MaxVit vison transformer model	Asian, Black, Indian, Latino Hispanic, Middle Eastern, and White	77%

III. PROPOSED METHOD

This section describes the proposed approach for ethnicity recognition using computer-vision techniques based on deep learning. There are two main limitations of the existing techniques described in the literature review section. First, most of the proposed techniques are limited to classifying up to four ethnic groups. Secondly, the proposed techniques are limited to the utilization of CNN models for the purpose of feature extraction. Thus, this paper proposes a model for classifying six ethnic groups i.e., Asian, Black, Indian, Latino Hispanic, Middle Eastern, and White by employing the MaxViT model which is a hybrid Vision Transformer based model capable of feature extraction and classification.

A. *Multi-Axis Vision Transformer (MaxViT)*

Initially transformers were proposed for the task of natural language processing [35], the prime feature of transformers is the self-attention mechanism which is the ability to capture semantic relations between data segments in a sequence. However, recently in the scope of computer-vison transformers have attracted considerable interest in the research community and several approaches have been proposed for image classification, segmentation, object detection, and generation. Thereby, Zhengzhong Tu et al. [9] proposed a Self-Attention mechanism named multi-axis self-attention (Max-SA) which can capture both local and global semantic relations between data segments. This is accomplished by decomposing the self-attention mechanism into window attention for local interaction and grid attention for global interaction. The Max-SA mechanism is a stand-alone attention module which can be adopted in any network architecture. Thus, The Max-SA module is the backbone structure of MaxViT model (see Fig. 1) coupled with Inverted Residual Block (MBConv) [36]. The model is available on Google Colab notebook (https://colab.research.google.com/drive/1UvseIP7zvFiysagSp4zfvt9f9ErHu-lo?usp=sharing).

MaxViT module uses the relative positional multi-head attention mechanism. The basic concept of an attention mechanism is to estimate the relevance of one data token to other data tokens in a sequence. In self-attention layer there are three trainable weight matrices (W^Q, W^K, W^V) from which three variables are generated by performing dot-product multiplication of the initial input variable (X_i) with learnable matrices represented as $(Q = XW^Q, K = XW^K, V = XW^V)$, from which attention layer output is represented as in Eq. (1), where d_k is input size [37].

$$Attention(Q, K, V) = sofmax\left(\frac{QK^t}{d_k}\right)V \qquad (1)$$

As for multi-head attention which is an extension of self-attention where the input is first partitioned into several segments and each segment is processed in parallel by a separate attention layer from which the output of each layer is considered as an attention head. Hence, multiple attention heads are aggregated as the final output allowing the model to capture various feature aspects of the input. As for the relative positional self-attention, an additional bias is concatenated with the output of the attention layer which incorporates positional importance of data tokens in a sequence.

The MaxViT module is composed of three main blocks. First, the MBConv with Squeeze-and-Excitation (SE) [38] block, window attention block, and grid attention block. The MBConv with SE is utilized to enhance the model efficiency and generalization, where MBConv are used to scale the model depth wise allowing it to capture complex features, and SE are used as channels wise self-attention mechanism that capture interdependencies between channels. The window attention block transforms the input feature map into non-overlapping windows to represent a confined attention by reshaping it $\left(\frac{H}{P} \times \frac{W}{P}, P \times P, C\right)$ where P is the window size. The grid attention block transforms the input feature map into uniform grid to represent a sparse attention by reshaping it $\left(G \times G, \frac{H}{G} \times \frac{W}{G}, C\right)$ where G is the grid size. Each of the attention blocks outputs are reshaped back to the initial input shape and passed through a multi-Layer perceptron block is illustrated in Fig. 1.

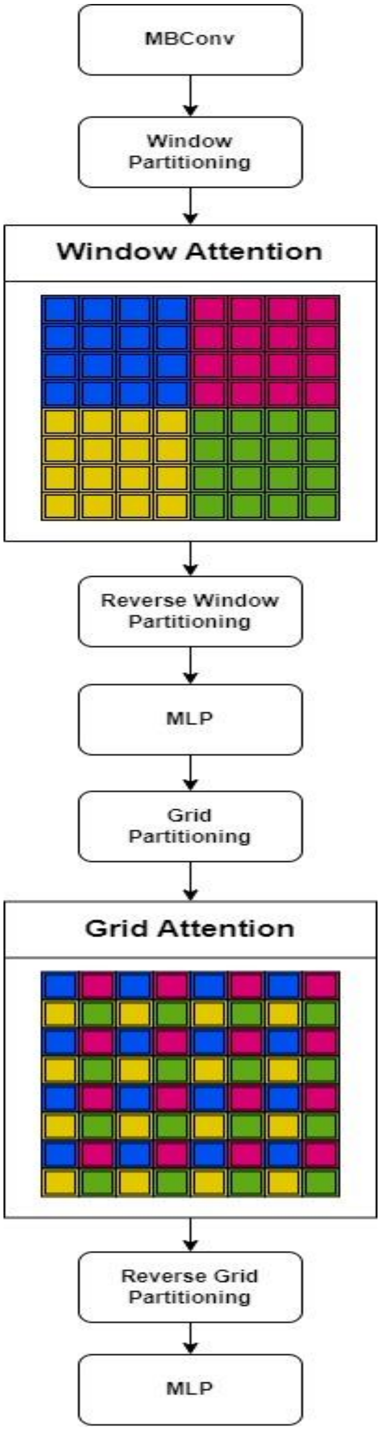

Fig. 1. MaxViT module attention mechanism.

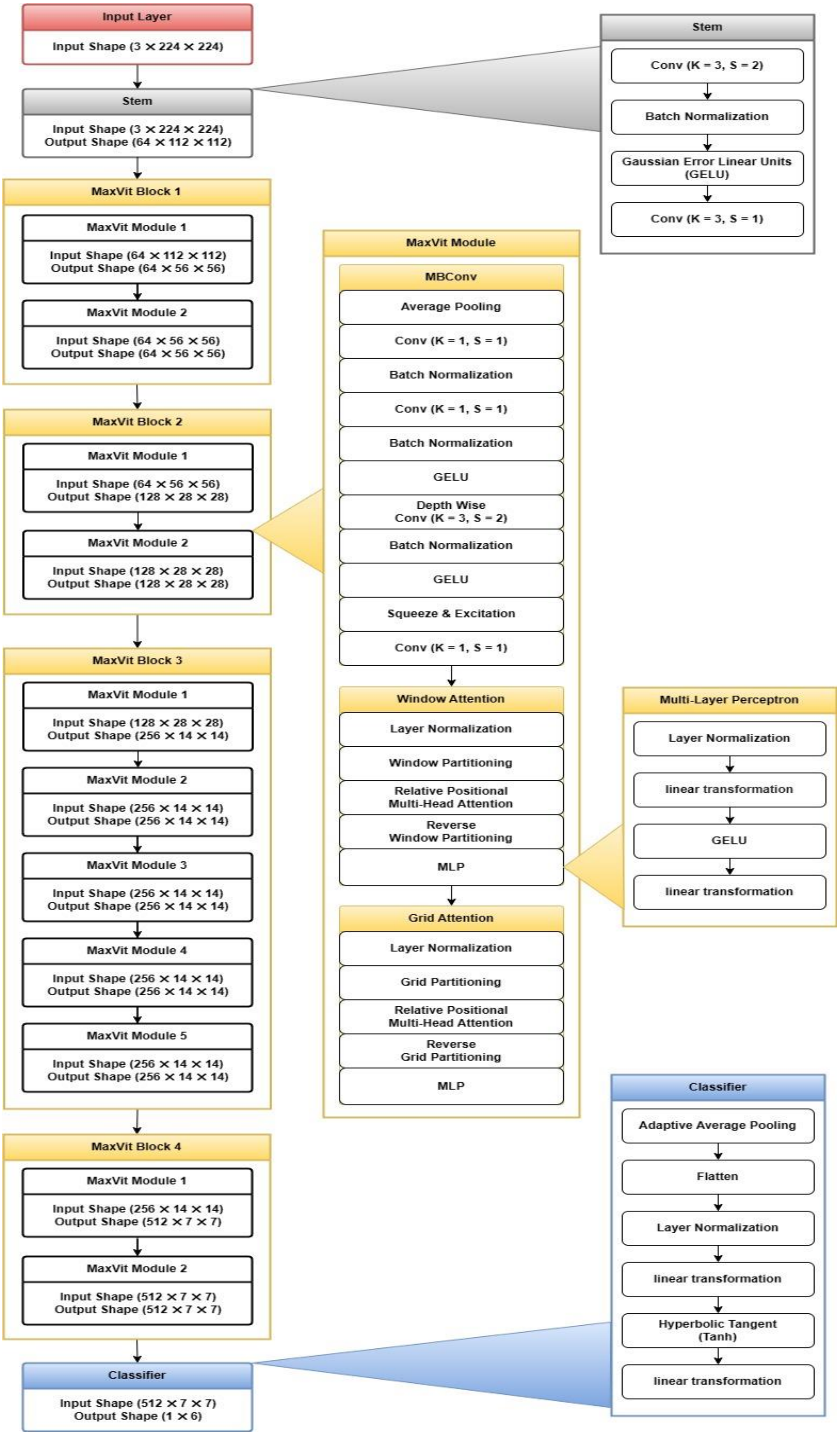
Input Layer
Input Shape (3 × 224 × 224)
Stem
Input Shape (3 × 224 × 224)
Output Shape (64 × 112 × 112)
MaxVit Block 1
MaxVit Module 1
Input Shape (64 × 112 × 112)
Output Shape (64 × 56 × 56)
MaxVit Module 2
Input Shape (64 × 56 × 56)
Output Shape (64 × 56 × 56)
MaxVit Block 2
MaxVit Module 1
Input Shape (64 × 56 × 56)
Output Shape (128 × 28 × 28)
MaxVit Module 2
Input Shape (128 × 28 × 28)
Output Shape (128 × 28 × 28)
MaxVit Block 3
MaxVit Module 1
Input Shape (128 × 28 × 28)
Output Shape (256 × 14 × 14)
MaxVit Module 2
Input Shape (256 × 14 × 14)
Output Shape (256 × 14 × 14)
MaxVit Module 3
Input Shape (256 × 14 × 14)
Output Shape (256 × 14 × 14)
MaxVit Module 4
Input Shape (256 × 14 × 14)
Output Shape (256 × 14 × 14)
MaxVit Module 5
Input Shape (256 × 14 × 14)
Output Shape (256 × 14 × 14)
MaxVit Block 4
MaxVit Module 1
Input Shape (256 × 14 × 14)
Output Shape (512 × 7 × 7)
MaxVit Module 2
Input Shape (512 × 7 × 7)
Output Shape (512 × 7 × 7)
Classifier
Input Shape (512 × 7 × 7)
Output Shape (1 × 6)
Stem
Conv (K = 3, S = 2)
Batch Normalization
Gaussian Error Linear Units (GELU)
Conv (K = 3, S = 1)
MaxVit Module
MBConv
Average Pooling
Conv (K = 1, S = 1)
Batch Normalization
Conv (K = 1, S = 1)
Batch Normalization
GELU
Depth Wise Conv (K = 3, S = 2)
Batch Normalization
GELU
Squeeze & Excitation
Conv (K = 1, S = 1)
Window Attention
Layer Normalization
Window Partitioning
Relative Positional Multi-Head Attention
Reverse Window Partitioning
MLP
Grid Attention
Layer Normalization
Grid Partitioning
Relative Positional Multi-Head Attention
Reverse Grid Partitioning
MLP
Multi-Layer Perceptron
Layer Normalization
linear transformation
GELU
linear transformation
Classifier
Adaptive Average Pooling
Flatten
Layer Normalization
linear transformation
Hyperbolic Tangent (Tanh)
linear transformation

Fig. 2. Architecture of MaxVit model.

The MaxViT model architecture is shown in Fig. 2. The MaxViT model architecture can be described as follows. First, the input layer which takes an input feature map of size (C, H, W) where C depicts the feature map channels/depth, H the feature map height, and W the feature map width. The stem layer uses convolutional layers to extract low-level features from the input and reduce its spatial dimensionality. Thus it reduces the computational complexity of the model. The MaxVit block which is composed of sequentially staked MaxViT modules where each block outputs half the resolution of the prior block with a doubled channels size. Finally, the classifier which transforms the multi-dimensional output into one-dimensional i.e., a feature vector. From then the feature vector is passed to a fully connected layer which performs linear transformation and outputs a prediction.

IV. Experiment and Results

This section describes the datasets used for model training and testing, the experiment conducted, and the results obtained. The experiments were implemented using PyTorch (2.0.0+cu118) for Python (3.10.5) and executed on a computer with Intel Core i7-6700 processor with 16 GB RAM, and RTX 3080 with 10-GB VRAM GPU.

A. Dataset

The experiments were conducted on a database created by merging three datasets FairFace [10], UTKFace [11], and Arab face dataset [12]. Dataset is described in Fig. 3 composed of six classes with sample sizes of 15,937 for Asian, 18,589 for Black, 18,074 for Indian, 14,988 for Latino Hispanic, 15,188 for Middle Eastern and 28,645 White, with a total of 111,421 samples split into 101,474 samples for training and 9,947 samples for testing. The ratio of training samples to testing samples per class is shown in Fig. 4. Random samples from each dataset are shown in Fig. 5.

B. Experiment

This section describes the configuration and hyperparameters used for the proposed model. The objective of this experiment is to employ the MaxVit transformer-based model for ethnicity recognition using facial images. The experiment utilizes transfer learning technique to reduce computational complexity and training time by reusing the pre-trained parameters of all the model layers excluding the classifier head which were modified to an output size of 6 hence the initial model is trained on ImageNet dataset [39] for object classification with an output size of 1000. Also, in the experiments all of the pre-trained model layers parameters are retrained.

Data Preprocessing: Typically, when utilizing transfer learning data must follow the same preprocessing pipeline used for training the initial model. Thus, for data preprocessing the first step is to resize the image to 224 × 224 pixels with center crop applied, and then a random horizontal flip of the image is applied with probability of 80% as a data augmentation. Next, image pixels values are converted from 0 to 255 to be between 0.0 and 1.0, where each of the color channels values represented as (Red, Green, Blue) are normalized by a mean of 0.485, 0.456, 0.406 and standard deviation of 0.229, 0.224, 0.225, which can enhance the model's learning process by standardizing the input. The specific values are often determined empirically based on the dataset being used. In this case, these values are used when trained on ImageNet dataset.

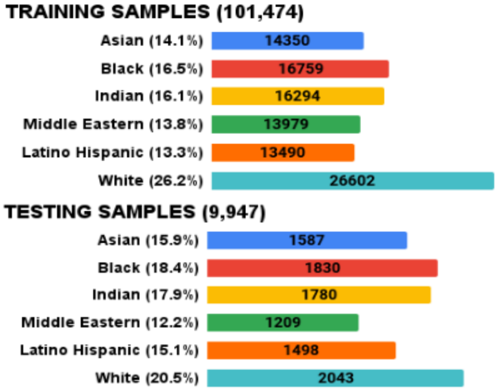

Fig. 3. Dataset overview.

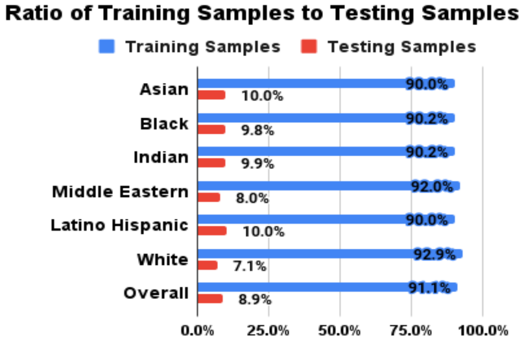

Fig. 4. Data split ratio.

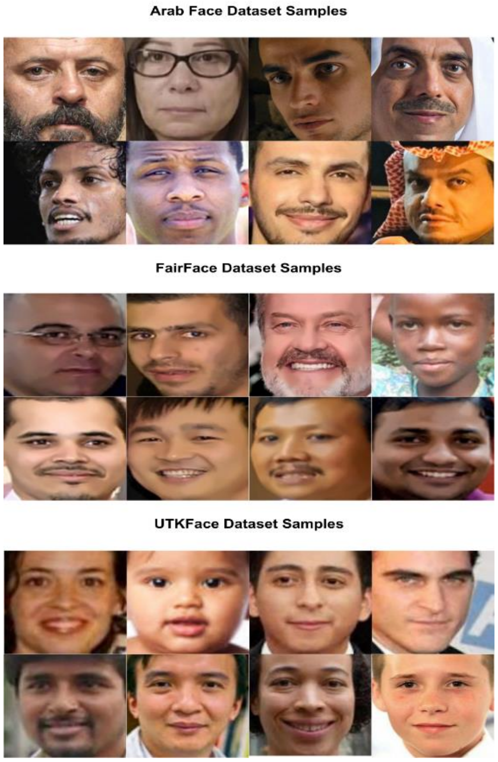

Fig. 5. Samples overview from each dataset.

Model hyperparameters: The model takes an input tensor shape of (B, C, H, W) where B stands for batch size and has the value of 20 images, C for color channels which is 3 for each image, H for the pixel height of each image that is 224, and W for the pixel width of each image that is 224. Based on the experiment an optimal batch size is between 16 and 20, thus for the purpose of reducing training time and fully utilizing hardware capacity the batch size is set as 20 images. A head dimension of 32 is used to represent the output feature map of the attention layers with partitioning size of 7 × 7 for both window and grid attentions, for the purpose of reusing the pre-trained parameters. Cross-entropy loss is used as a loss function to measure the dissimilarity between predicted probabilities and the actual targets. As for model parameters optimization the Adadelta algorithm is implemented with a learning rate of 0.1. Adadelta is an adaptive learning rate technique [40] which dynamically and automatically adjusts the learning rates on a per-parameter level, thus based on the experiment with Adadelta optimizer the learning rate value does no substantial impact on the learning process unless extreme values are used.

C. Results

In the main experiment the model was trained for 15 epochs achieving the highest classification accuracy of 0.772 for classifying six ethnic groups of Asian, Black, Indian, Latino Hispanic, Middle Eastern, and White. Additional experiments are conducted for a comparison in which four CNN models are trained using the same dataset. These models are a pre-trained VGG-Face model based on Vgg-16 architecture [41] which is developed for face recognition with over two million faces images. A pre-trained VGG-Face2 model based on ResNet-50 architecture [17] which is also developed for face recognition but with over three million faces images. A pre-trained EfficientNet-V2 model [42] for object classification is also based on MBConv. Additionally for the purpose of testing MaxVit model scalability an experiment is conducted by training the proposed model on three ethnic classes i.e., Black, White and others which is a merged class of all the remaining categories. For training the sample sizes used are 17,015 samples for Black, 17,099 samples for White, and 18,458 samples for the merged class. For evaluation the sample sizes used are 1,300 samples for black, 1,300 samples for white and 1,500 samples for the merged class. The model achieved a classification accuracy of 0.835. Lastly for comparison the same experiment is conducted with three classes using the AlexNet model [32] which achieved the classification accuracy of 0.782. The results are shown in Fig. 6. Additionally, the classification accuracy of top two predicted classes is shown in Fig. 7 where the proposed MaxVit model achieves the highest score of 91.3%. A comparison of model size in terms of parameters size is shown in Fig. 8, where the proposed MaxVit model being the smallest model in terms of parameters size. Hence, in terms of performance smaller models require lower computational capacity thus being more efficient in terms of speed and size on disk. Confusion matrices are shown in Fig. 9 describing the models classification performance of 9,947 samples for six classes.

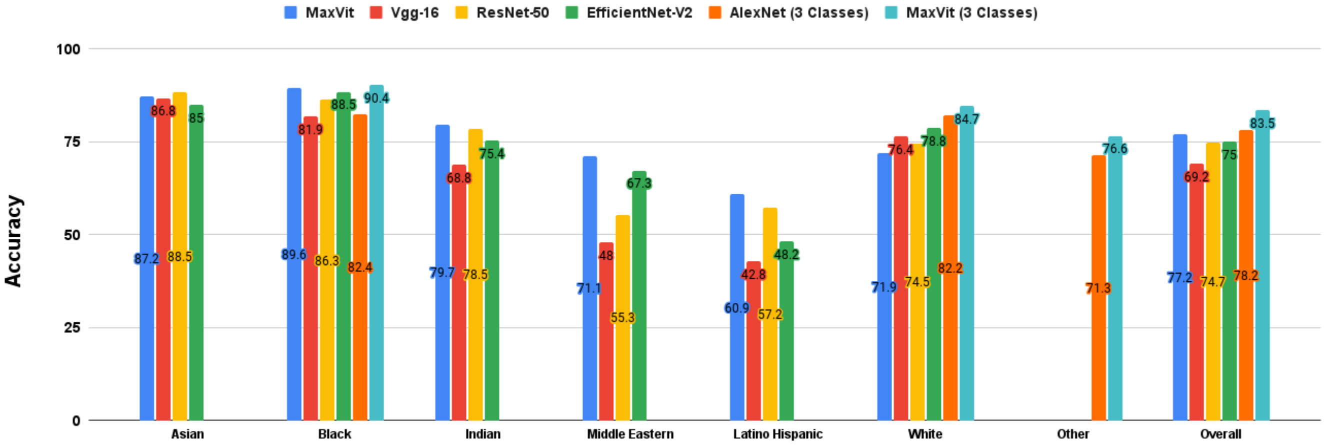

Fig. 6. Models classification accuracies.

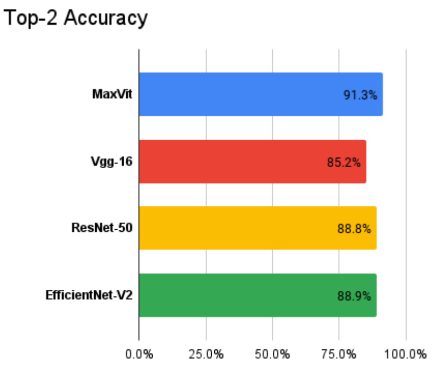

Fig. 7. Top two predicted classes accuracy scores.

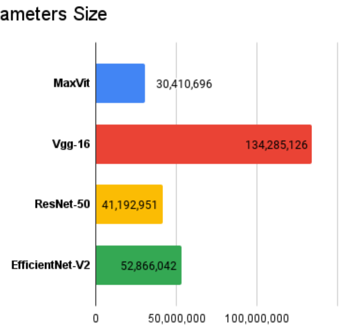

Fig. 8. Models parameters size.

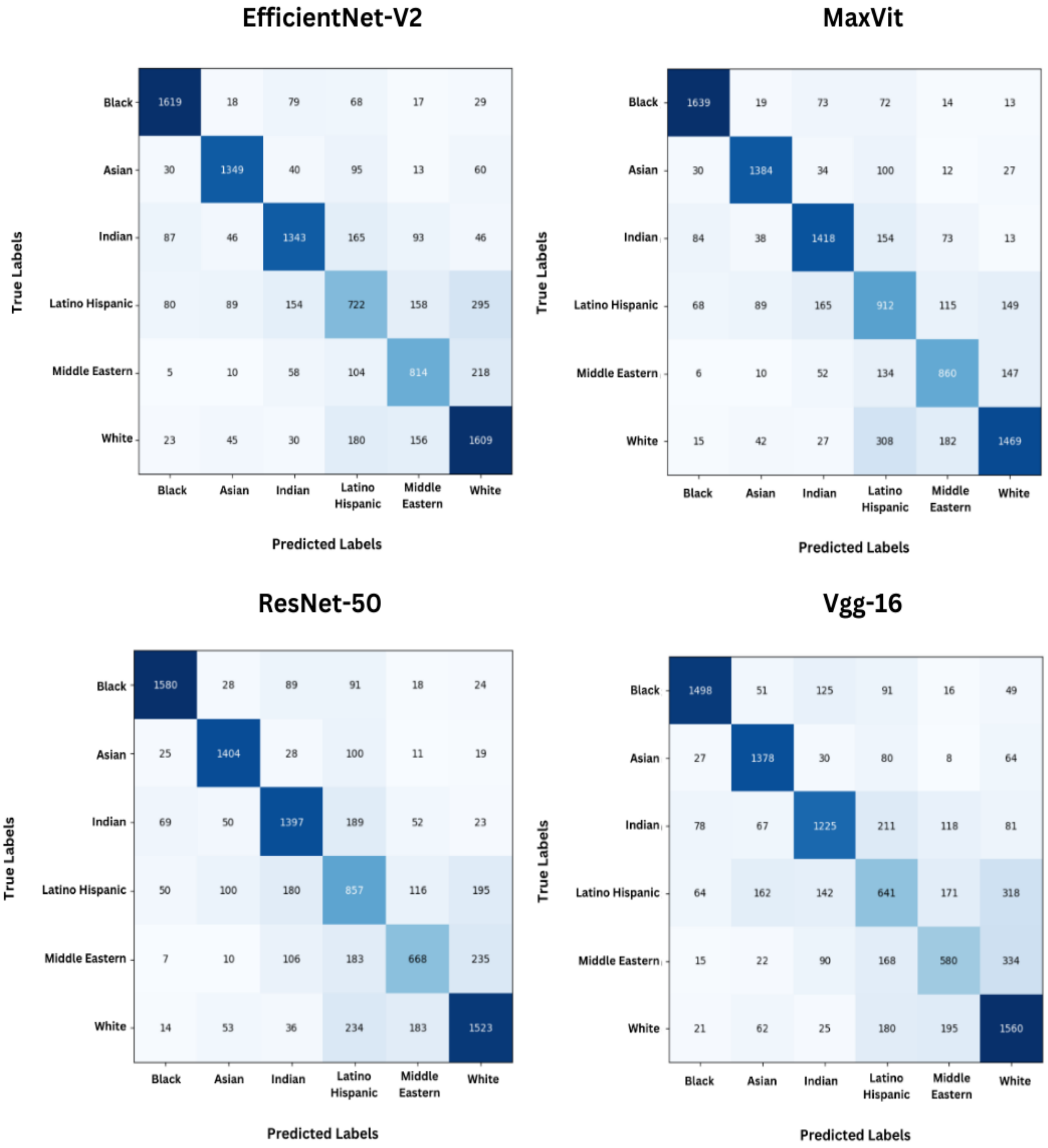

Fig. 9. Confusion matrices.

Based on observation, the model’s misclassification for both of Latino Hispanic, and Middle Eastern is noteworthy. This due to the high overlapping diversity between the three ethnic groups of White, Latino Hispanic, and Middle Eastern which are merely considered multiracial groups [43]. Thus, considerable efforts are required for the creation of a representative dataset for such ethnic groups, which certainly could improve the performance of ethnicity recognition models. However, in the conducted experiments the proposed MaxVit model achieves better generalization compared to other models.

V. Conclusion

This paper addresses the two common limitations of research in the field of race recognition. First, a large database has been created with six racial categories i.e., Asian, Black, Indian, Latino Hispanic, Middle Eastern, and White. Second, it has proposed the usage of a vision transformer named MaxVit as an ethnicity recognition model using facial images. It achieves a classification accuracy of 77.2% and better generalization than other recent works.

The research area of race and ethnicity recognition is still unsaturated, mainly from the aspect of racial or ethnic groups diversity, as the number of pre-defined racial categories is limited by the available datasets. This could be particularly problematic for individuals who have mixed racial backgrounds, thus multiracial classification is noteworthy as racial facial traits are noticeably overlapped for most of population individuals. Therefore, a considerable effort should be devoted towards such aspects, which certainly contribute to the advancement of the research area.

Acknowledgment

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A Driving Area Detection Algorithm Based on Improved Swin Transformer

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***Abstract*—Drivable area or free space detection is an essential part of the perception system of an autonomous vehicle. It helps intelligent vehicles understand road conditions and determine safe driving areas. Most of the driving area detection algorithms are based on semantic segmentation that classifies each pixel into its category, and recent advances in convolutional neural networks (CNNs) have significantly facilitated semantic segmentation in driving scenarios. Though promising results have been obtained, the existing CNN-based drivable area detection methods usually process one local neighborhood at a time. The locality of convolutional operation fails to capture long-range dependencies. To solve this problem, we propose an improved Swin Transformer based on shift window, named Multi-Swin. First, an improved patch merging strategy is proposed to enhance feature interactions between adjacent patches. Second, a decoder with upsampling layer is designed to restore the resolution of the feature map. Last, a multi-scale fusion module is utilized to improve the representation ability of global semantic and geometric information. Our method is evaluated and tested on the publicly available Cityscapes dataset. The experimental results show that our method achieves 91.92% IoU in road segmentation detection, surpassing state-of-the-art methods.**

Keywords—CNNS; driving area detection; multiscale fusion; semantic segmentation; Swin Transformer

I. INTRODUCTION

With the rapid development of computer technology, autonomous driving has entered into real life. Driving area detection aims to accurately determine the current accessible area of vehicles in complex road environments using relevant technologies, which is a critical research area within the field of autonomous driving. Given the crucial role of the drivable area detection algorithm in ensuring the safety and efficiency of vehicle driving on the road, there is an urgent need to improve the accuracy of road detection.

The existing driving area detection methods can be divided into traditional methods and learning-based methods. Traditional methods use the pavement features of 2D images to segment roads. For example, Shi et al. [1] use the road color characteristics and vanishing points to detect the road boundary. Some researchers use edge detection operators to extract the edge boundary of the road and segment the road surface [2], [3]. Though traditional methods can detect driving areas in real time, they are not suitable for complex situations where the road surface features are not obvious.

Learning-based methods typically rely on semantic segmentation to achieve their goals. Semantic segmentation is a pixel-level technology that acts on each pixel of an image to predict its category. This prediction preserves the edge and semantic information of the original image, which is beneficial for enabling autonomous vehicles to understand the scene. As an exemplary approach, ERFNet [4] has demonstrated remarkable performance in road segmentation by incorporating residual layers and decomposition convolutions. Additionally, SNE-RoadSeg [5], data fusion CNN architecture, leverages RGB images and inferred surface normal information to accurately detect driving areas. Despite the success of existing learning-based techniques, the convolutional feature extraction is often criticized for its inability to capture long-range dependencies, which can impede the semantic segmentation performance.

Compared to convolution-based feature extraction methods, Transformer [6] can learn the relationship between global pixels, rather than just their local neighborhood. Additionally, the number of operations required to calculate the correlation between two positions is independent of the distance. For instance, the Swin Transformer [7] has achieved impressive results in image classification, object detection, and semantic segmentation thanks to its window attention and layered design. However, Transformer has not yet been applied to driving area detection. It should also be noted that the current fusion strategy reduces the information interaction between adjacent patches during the down sampling process.

This paper aims to address the limitation of convolution in capturing long-range dependency information. To achieve this, a pure attention model is proposed to replace the convolution operation with a gradually decreasing spatial resolution. To be specific, the input image is first divided into patches of the same size and the corresponding position encoding for each pixel is generated using a linear embedding layer. An encoder composed entirely of Swin Transformer is used to process the patches and a new patch fusion strategy is proposed to improve the information interaction between adjacent patches in the same window. A multi-scale fusion module is then employed to enhance the expression ability of the global semantic and geometric information of the feature map obtained from the encoder. Finally, a decoder with an up-sampling operation is designed to restore the resolution of the feature map and complete pixel-level segmentation prediction. The road segmentation experiment is conducted on

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publicly available Cityscape dataset [8], and the experimental results prove the effectiveness of the proposed method.

II. Related Works

A. Semantic Segmentation

Convolution neural network (CNN) [9] is a kind of feedforward neural network with convolution computation and depth structure, which was originally designed for image classification tasks. In 2015, Long et al. [10] first applied convolution operations to semantic segmentation tasks in FCN. They use 1x1 convolution to replace the full connection layer in the convolutional network. And the feature map is upsampled to achieve end-to-end network segmentation. U-Net [11] adopts a fully symmetrical encoder-decoder structure on the basis of FCN, and deepens the decoder by stacking convolutional layers. It effectively improves the performance with only a small amount of training data. SegNet [12] transfers the maximum pooling index to the decoder, which improves the segmentation resolution and shows better performance than FCN. Furthermore, the emergence of the residual layer [13] can avoid the degradation of the deep network and achieve very high accuracy with network that stack a large number of layers [14]. DANet [15] uses the Xception network as the backbone, and adds a full connection module based on the attention mechanism at the end to retain the more receptive field. SENet [16] automatically obtains the importance of each channel by explicitly modeling the interdependence between feature channels and divides the attention mechanism into two very key operations, Squeeze and Excitation. While decreasing the number of parameters and computational requirements, the accuracy of the algorithm is improved.

B. Multi-Scale Fusion

Recently, several approaches have been presented to tackle the limited receptive field problem in FCNs and their variations. DeepLab [17] applies atrous spatial pyramid pooling (ASPP) in the spatial dimension and leverages conditional random fields (CRFs) to refine the output results. FPN [18] asserts that small targets require the use of larger-scale feature maps due to inadequate resolution information provided by smaller ones, but downsampling losses in deeper images lead to excessive information loss, potentially disregarding small target details. Zhao et al. [19] propose utilizing dilated convolutions to augment the ResNet architecture. Their PPM module facilitates multi-scale feature fusion by acquiring diverse background information across regions. DeepLabV3+ [20] builds on an enhanced Xception [21] backbone and incorporates the decoder module from DeepLabV3 [22], further integrating low-level and high-level features to improve segmentation boundary accuracy. Qin et al. [23] introduce an autofocus convolutional layer, an attentive variant of ASPP, to enhance multi-scale feature extraction capabilities. This layer dynamically learns the weights of different branches via an attention mechanism, adapting the receptive field size for effective multi-scale feature extraction. Gu et al. [24] utilize dual parallel encoders to extract information at varied scales, subsequently merging them using a decoder. With a UNet backbone, each encoder processes images of dissimilar resolutions to acquire feature maps at differing scales.

C. Vision Transformer

ViT [25] uses Transformer for vision tasks for the first time. The 2D image is divided into patches of the same size and expanded into 1D sequences by pixels. The position coding of each pixel is obtained through the linear embedding layer and then input into the encoder. It shows the great potential of Transformer in the field of vision. However, ViT must first be pretrained on a large-scale dataset. Different from ViT, DEiT [26] uses an appropriate training method and distillation technique to solve this problem. DEiT can learn inductive biases based on CNN thanks to the distillation principle, which enhances its capacity to interpret image-type data. SETR [27] achieves excellent semantic segmentation performance with three optional decoding algorithms and a Transformers-based encoder.

The global attention used in Transformer requires a lot of computing resources. Swin Transformer adopts sliding window and layered architecture to solve this problem. The sliding window restricts the attention calculation to one window, introduces the locality of CNN convolution operation and reduces the amount of calculation. It achieves the impressive results on multiple tasks in the visual field. SegFormer [28] combines Transformer encoder and MLP decoder. The position encoding will result in performance degradation because the testing and training resolution are different. To address this issue, SegFormer utilizes a 3x3 deepwise convolutional layer to transmit positional information. The proposed MLP decoder is utilized to combine local and global attention by aggregating the multi-scale features of the encoder output.

D. Driving Area Detection

The existing driving area detection methods can be divided into traditional methods and deep learning-based methods. The information about the pavement features in the 2D image is extracted and segmented by the conventional driving area detection technique. For example, Shi et al. [1] identified road borders using vanishing points and road color attributes. Gao et al. [29] proposed a real-time vision technique based on the color cue training model of continuous frames to identify the driving area in the presence of shadows, lane markers, or unstable lighting. Yao et al. [30] identify drivable area with Support Vector Machine (SVM) and achieve 82.51% F1-score on KITTI dataset [31]. Deep learning driving area detection makes use of semantic segmentation as a key tool. A multitask CNN network was introduced by Pizzati et al. [32] to determine the available space in each lane. The network can operate in real-time thanks to ROS-based calculation. Qiao et al. [33] built the architecture using the characteristic pyramid network and the spatial pyramid pool module based on the ResNet network. It was able to achieve 84.58% IoU on the BDD100K datasets. Choi et al. [34] proposes a network using accumulated decoder features, called ADFNet, which operates using only decoder information, with no skip connections between encoder and decoder. Han et al. [35] proposed a new partitioned network, EdgeNet. It includes a class aware edge loss module and a channel attention mechanism. More than

70% of IoU was obtained on the Cityscapes dataset. In order to overcome the issues of limited anti-noise ability and inadequate segmentation of small-scale objects, Dong et al. [36] proposed an approach using a generative adversarial network (GAN [37]) in conjunction with an ERFNet model.

While these approaches have yielded good experimental results in the drivable area detection domain, they do not address the problem of poor long-range information reliance due to convolutional kernel restrictions.

III. METHOD

A. Architecture Review

The architecture of the driving area algorithm of the improved Swin Transformer proposed in this paper is shown in Fig. 1, which is composed of an encoder, a decoder, and a multi-scale fusion module. The network processing flow is as follows： First, the RGB input images are separated into identically sized, non-overlapping patches. Second, linear embedding layer generates patch embedding. Then, the encoder takes these embeddings as input to generate feature maps. Next, a multi-scale fusion module is introduced between the encoder and decoder to improve the representation ability of the feature map. After that, the decoder restores the original image resolution. Finally, pixel-level segmentation prediction is produced via a 1x1 convolutional Layer. Below, we'll go into more depth about each module.

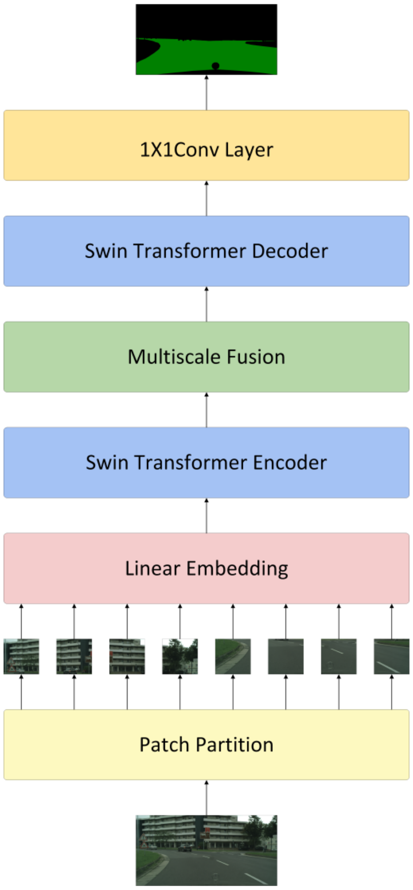

Fig. 1. Network structure.

B. Preprocessing

The input of multi-head self-attention (MSA) is 1D sequence, but there is a mismatch between 2D image and 1D sequence. The input image needs to be sequentialzed. Expanding the image pixel values into a 1D sequence is a direct way. However, the computing complexity increase sharply if the input is a high-resolution image. To solve this problem, we divide the input images into size 4X4, non-overlapping patches, which is similar to prior works [7], [21]. By further mapping each vectorized patch into a C dimensional embedding space with a linear embedding layer, we obtain a 1D sequence of patch embeddings for an input image.

C. Encoder

As shown in Fig. 2, the encoder consists of Swin Transformer blocks and patch merging layers. The supplied image is split into 4X4 patches. The Swin Transformer blocks perform feature representation learning on the input images, and generate a feature map. The patch merging layers down sample the received feature map to expand the receptive field. The layer processing of our proposed encoder is shown in Table I.

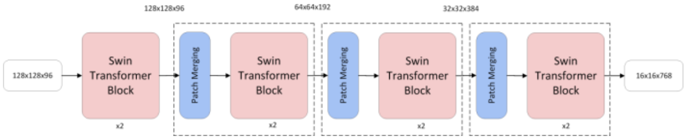

Fig. 2. Detailed display of encoder.

TABLE I. LAYER DISPOSAL OF OUR PROPOSED ENCODER

Layer	Type	Out-F	Out-Res
1	Patch Partition	48	$\frac{H}{4}$ x $\frac{W}{4}$
2	Linear Embedding	C	$\frac{H}{4}$ x $\frac{W}{4}$
3-4	Swin Transformer Block	C	$\frac{H}{4}$ x $\frac{W}{4}$
5	New Patch Merging	2C	$\frac{H}{8}$ x $\frac{W}{8}$
6-7	Swin Transformer Block	2C	$\frac{H}{8}$ x $\frac{W}{8}$
8	New Patch Merging	4C	$\frac{H}{16}$ x $\frac{W}{16}$
9-10	Swin Transformer Block	4C	$\frac{H}{16}$ x $\frac{W}{16}$
11	New Patch Merging	8C	$\frac{H}{32}$ x $\frac{W}{32}$
12	Swin Transformer Block	8C	$\frac{H}{32}$ x $\frac{W}{32}$

1) Swin Transformer block: Fig. 3 illustrates the structure of Swin Transformer block. It is consisted of LayerNorm layer (LN), multi-head self-attention (MSA), residual connection, and MLP layer with nonlinear GELU. As indicated in Fig. 3, Swin Transformer block is computed as follows:

$$\hat{y}^{l} = W - MSA(LN(y^{(l-1)})) + y^{(l-1)} \tag{1}$$

$$y^{l} = MLP(LN(\hat{y})) + \hat{y}^{l} \tag{2}$$

$$\hat{y}^{(l+1)} = SW - MSA(LN(y^l)) + y^l \tag{3}$$

$$y^{(l+1)} = MLP(LN(\hat{y}^{(l+1)})) + \hat{y}^{(l+1)} \tag{4}$$

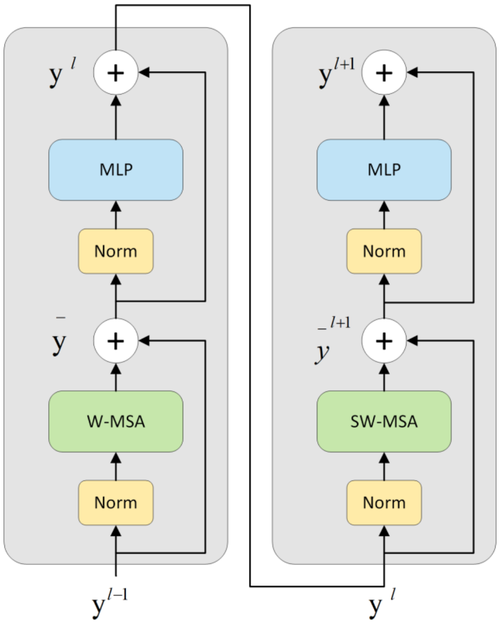

Fig. 3. Illustration of Swin Transformer block inside encoder and decoder.

where, ŷ is the output after (S) W-MSA, and y is the output after MLP. Instead of global attention, the window attention mechanism is used to reduce computational complexity. Compared to the quadratic complexity of global attention, the computational complexity of the small window grows linearly. The window-based multi-head self-attention (W-MSA) and shift window-based (SW-MSA) are utilized to improve cross-window connection. Self-attention formula is as follows:

$$Attention(Q,K,V) = SoftMax(\frac{QK^T}{\sqrt{d}} + B)V \tag{5}$$

where, Q, K, and V represent query, key, and value matrix, d represents dimension, and B represents offset. Attention is shown in Fig. 4.

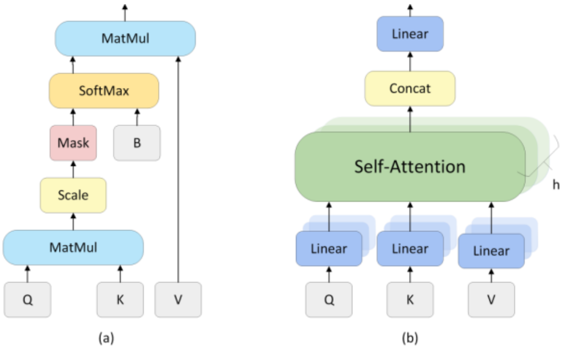

Fig. 4. (a) Self-Attention. (b) Multi-Head self-attention.

2) New patch merging: The patch merging process is shown in Fig. 5. This module aims to down sample the feature map received from the Swin Transformer blocks. It reduces calculation, and realizes hierarchical design. After the merging layer, the resolution of feature map becomes half of the original. First, the pixel values are taken at intervals in the row and column directions of the feature map to form four new tensors. As indicated in Fig. 5, two adjacent pixels on the new feature map are not adjacent in the original feature map, which reduces information interaction during fusion. To improve the interaction between adjacent pixel points, we add a pooling layer in the fusion stage. A new tensor with a channel dimension of 5C is created by concatenating the output of the pooling layer and the feature maps generated from the down sampling. The resolution of the feature map is finally changed using the fully connected layer. The problem of lack of information interaction caused by capturing pixels at intervals is relieved since the feature map produced by the pooling layer has the global features of the input.

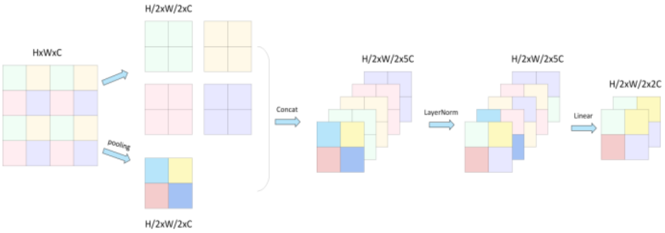

Fig. 5. The process of patch merging.

D. Multi-scale Fusion

The objects in the image are range in size, and each object has a unique set of features. Shallow features can be used to differentiate simple objects, while deep features can be used to separate complex targets. Combining data from various levels is better suited for complicated tasks since the shallow network prioritizes details while the high-level network prioritizes semantic information. In order to improve the capacity to convey global semantic and geometric information, we design a multi-scale fusion module. It combines the output of each group of Swin Transformer Blocks between the encoder and decoder. The multi-scale fusion module is shown in Fig. 6. Given four feature maps produced by Swin Transformer blocks at different stages, the down sampling operation is first performed on the three feature maps with high-resolution. Secondly, 1x1 conv layer is used to map the feature maps of different dimensions to the same dimension. Finally, four groups of feature maps are concatenated to form a new feature map. The obtained feature map has stronger representation ability because it fuses feature information from different levels.

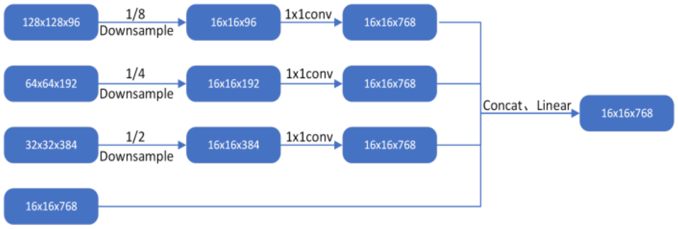

Fig. 6. Details of multi-scale fusion.

E. Decoder

Similar to the encoder, the decoder is composed of Swin Transformer blocks and patch extension layers. Fig. 7 depicts details of the decoder. Among them, the Swin Transformer block is consistent with the encoder, and the patch expansion layer upsamples the feature maps. It has been suggested by SETR that restoring the resolution to its original size in one-step might be interfered by noise. Instead of one-step upscaling, we consider a progressive upsampling technique. Each time a patch expansion layer is applied, the input feature map is increased to 4x resolution. Then feature map resolution is restore to its original size using a 2X upsampling layer at the end of the decoder. To output pixel-level segmentation prediction, a 1x1 convolutional layer is employed. Table II shows the layer processing of our proposed decoder.

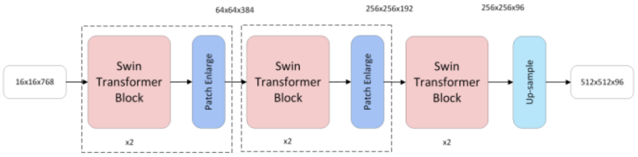

Fig. 7. Detailed display of decoder.

TABLE II. LAYER DISPOSAL OF OUR PROPOSED DECODER

Layer	Type	Out-F	Out-Res
1-2	Swin Transformer Block	4C	$\frac{H}{32} x \frac{W}{32}$
3	Patch Enlarge	4C	$\frac{H}{8} x \frac{W}{8}$
4-5	Swin Transformer Block	2C	$\frac{H}{8} x \frac{W}{8}$
6	Patch Enlarge	2C	$\frac{H}{2} x \frac{W}{2}$
7-8	Swin Transformer Block	C	$\frac{H}{2} x \frac{W}{2}$
9	Up-sample	C	H x W

IV. EXPERIMENT

A. Dataset and Experimental Setup

The dataset chosen for this study is Cityscapes. The primary goal of Cityscapes dataset is to provide an image segmentation dataset in an unmanned driving environment, so that researchers can evaluate the performance of algorithms to understand the semantic information of the urban environment. Cityscapes provides 5000 fine annotation images and 20,000 rough annotation images, with a total of 33 categories of annotation items, including 50 street scenes of different cities in various scenarios, backgrounds, and seasons. There are 19 commonly employed categories. Drivable area detection aims to identify the driving area on the road, so we only use the datasets that contain annotations about the road. As a result, there are only two categories in this experiment: drivable area and background. Fig. 8 displays cityscape datasets. There are fine-labeled and coarse-labeled images in the Cityscapes dataset. Although the segmentation accuracy of coarse labeled images is not as good as that of fine labeled images, they still contribute to model training. Therefore, we train the ADE20K pretrained model released by Swin Transformer on roughly labeled Cityscapes images. And use it as a pre-trained model to train fine-label dataset.

Python 3.8 and Pytorch 1.12.1 are used to implement the model. The window size based on shift window attention is set to be 7, the patch size is set to 4, and the input image size is set to 512x512. We trained our model on a NVIDIA RTX2080Ti GPU. Our backpropagation model is optimized using the AdamW optimizer with a momentum of 0.9 during training. The batch size is 8 and the learning rate is 1e-4.

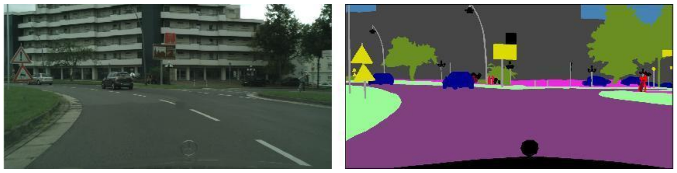

Fig. 8. Cityscapes datasets.

B. Evaluation Metrics

The commonly used Intersection over Union (IoU) [38] index, pixel level accuracy, and precision are used to evaluate the experimental results. We use the pixel level for the three test indicators. IoU is the ratio of the intersection sum of the predicted result and the true value:

$$\mathrm{IoU} = \frac{TP}{TP + FP + FN} \tag{6}$$

Pixel level accuracy is the ratio of correctly classified pixels to the total number of pixels in the image:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{7}$$

The precision rate is the probability that all predicted positives are actually positives:

$$\mathrm{Pr}\,ecision = \frac{TP}{TP + FP} \tag{8}$$

where, TP, TN, FP and FN represent the pixel level true positive, true negative, false positive and false negative indicators,respectively. Positive refers to the labeled part (driving area), while negative refers to the part of the non-object label (which can be directly understood as the background).

C. Performance Evaluation

In this section, we qualitatively compare our proposed model with state-of-the-art semantic segmentation models. Each model was trained for about 200 epochs until convergence of the loss function. Evaluation was performed on the Cityscapes test set, consisting of 1525 images, at a resolution of 512x512. Experimental results for the Cityscapes dataset are shown in Table III. Our method demonstrates superior performance in category IoU when compared to HRNet [39] and U-Net, and excels in pixel-level accuracy and precision over other models. Specifically, it outperforms HRNet by 0.2%, 0.9%, and 0.63% in these metrics, and has a 0.15%, 0.88%, and 0.44% advantage over U-Net. Despite having a minor disadvantage in the IoU metric against DeepLabV3+, our method ranks first in the other two metrics with respective leads of 0.26% and 0.16%. These results support our claim that our method improves classification accuracy.

The semantic segmentation outcomes on the Cityscapes dataset are depicted in Fig. 9, where (a) is Original driving scene images, (b) is Ground truth annotations, (c) is Road segmentation results of our model. (d) Road segmentation results of DeepLabV3+, (e) is Road segmentation results of HRNet and (f) is Road segmentation results of UNet. The segmentation results reveal that our approach can accurately demarcate the road and surrounding objects within the driving region. In contrast to other techniques, our method provides better predictions for the edges of the drivable area and background. This superiority can be attributed to the fact that the attention mechanism captures long-range semantic information, achieving better performance than convolutional networks in edge detection. Hence, our method excels in learning edge pixels, resulting in higher pixel prediction accuracy and overall performance than other networks.

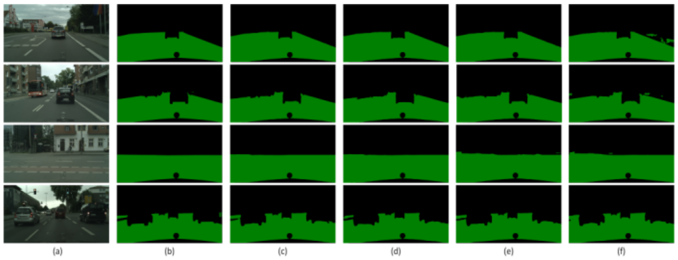

Fig. 9. Examples of road segmentation results on cityscapes dataset.

TABLE III. EVALUATION RESULTS ON THE CITYSCAPES TEST SET FOR ROAD SEGMENTATION

Models	IoU (%)	PA (%)	Precision (%)
Multi-Swin	91.92	**96.79**	**96.19**
HRNet	91.72	95.89	95.56
DeepLabV3+	**92.25**	96.53	96.03
U-Net	91.77	95.91	95.75

D. Ablation Study

In this section, we conduct ablation experiments on our proposed driving area detection algorithm to verify the effectiveness of different modules. From the perspective of patch fusion strategy, multi-scale fusion module and decoder, we conduct comparative experiments.

1) New patch merging: To substantiate the efficacy of the suggested patch fusion strategy, we replaced the patch merging layers with those from the original Swin Transformer, leaving the remaining networkarchitecture unmodified. The experimental outcomes are outlined in Table IV. From the data presented in Table IV, one can observe that our method surpasses the original Swin Transformer patch merging technique in all three examined metrics, resulting in improvements of 0.31%, 0.12%, and0.27%, respectively. This modification mitigates the insufficiency of information interaction during the fusion procedure to some degree, ultimately improving road segmentation accuracy.

TABLE IV. EXPERIMENTAL RESULTS OF FUSION STRATEGY

Models	IoU (%)	PA (%)	Precision (%)
Multi-Swin	**91.92**	**96.79**	**96.19**
Swin	91.61	96.67	95.92

2) Multi-scale fusion module: Our multi-scale fusion module's effectiveness is proven throughseveral experiments, including: a) substituting the proposed module with alternative multi-scale fusion techniques like ASPP and PPM, and b) removing the fusion module entirely. ASPP relies on multiple parallel dilated convolutional layers operating at varying dilation rates to extract features at different scales, which are then processed independently and merged into the final result. By constructing convolutional kernels with varying receptive fields through different dilation rates, ASPP captures object information across scales. On the other hand, PPM is designed to gather background information from multiple regions, addressing the lack of effective strategies to exploit global context in feature fusion. The experimental results are displayed in Table V. As illustrated in the table, our method yields the most favorable outcomes across all three metrics. Relative to ASPP, our fusion module shows significant improvement across all three metrics with gains of 0.51%, 1.28%, and 0.86%, respectively. When comparing against PPM, our fusion module exhibits performance advantages of 0.87%, 1.53%, and 1.21% for the same three metrics. Therefore, our proposed multi-scale fusion module aligns better with our network's design and enhances the accuracy of drive area detection.

TABLE V. EXPERIMENTAL RESULTS OF MULTI-SCALE FUSION MODULE

Models	IoU (%)	PA (%)	Precision (%)
Multi-Swin	**91.92**	**96.79**	**96.19**
Detachment	90.85	94.89	94.63
ASPP	91.41	95.51	95.33
PPM	91.05	95.26	94.98

3) Network structure: Swin Transformer Blocks serve as the primary components of both the encoder and decoder. To assess the effectiveness of our decoder, we substituted it with a Multi-Layer Perceptron (MLP), which includes an input layer, output layer, and several hidden layers. The MLP decoder utilizes GELU as a nonlinear activation function and restores the resolution of the input feature map to its initial dimensions. Results presented in Table VI reveal that our method outperforms MLP decoders across all three tested metrics, yielding boosts of 1.89%, 1.46%, and 2.05% for IoU, PA, and Precision, respectively. This validates the efficacy of our proposed decoder.

TABLE VII. EXPERIMENTAL RESULTS OF DECODER STRUCTURE

Models	IoU (%)	PA (%)	Precision (%)
Multi-Swin	**91.92**	**96.79**	**96.19**
MLP	90.03	95.33	94.14

E. Discussion

This paper presents the outcomes of four distinct experiments: a comparison test using cutting-edge techniques, as well as three separate sets of experiments employing the suggested drivable region recognition algorithm for purposes of elimination. These experiments show that our proposed algorithm achieves exceptional results in the realm of detecting drivable areas, with measurements such as Precision and PA reaching high levels of 96.19% and 96.79%, respectively, placing them at the forefront of comparable efforts. Additionally, the value of IoU was determined to be 91.92%. The experiments carried out for the purpose of eliminating variables confirmed the effectiveness of the various components put forth in this paper. Specifically, the novel patch fusion strategy served to enhance the interplay between neighboring points of interest, the multi-scale fusion module successfully combined more contextually relevant semantic information, thus increasing the expressiveness of feature maps, and lastly, the decoder employed in this work effectively restored the resolution of the feature map layer by layer, thereby mitigating any potential interference caused by noise and better suiting the overall architecture of the network described in this paper. Ultimately, these findings suggest that the methodology introduced in this study improves upon the accuracy of detecting drivable regions and could play a valuable role in furthering the application of deep learning within the domain of autonomous driving.

V. CONCLUSION

In this paper, an enhanced Swin Transformer based semantic segmentation algorithm is proposed. The proposed method is based on encoder-decoder framework. Different from other semantic segmentation networks, we use Swin Transformer as the main body of encoder and decoder. It is applied to the field of drivable area detection for the first time. Meanwhile, the patch merging strategy is improved to enhance the feature interaction between adjacent patches. We design a decoder with an upsampling layer to recover the resolution of the feature maps. Finally, a multi-scale fusion module between the encoder and decoder is used to optimize the expressiveness. We use the publicly accessible Cityscapes dataset for training and testing, and compare our algorithm with state-of-the-art semantic segmentation networks to demonstrate the feasibility and usability of the proposed method. Experimental results indicate that the enhanced Swin Transformer-based method outperforms other well-known algorithms in terms of IoU metrics, achieving higher levels of pixel level accuracy and precision.

Even while the Multi-Swin method has produced ground-breaking results in terms of the accuracy of drivable area recognition, it still has several issues that need to be fixed. In particular, compared to conventional convolutional networks, the use of attention mechanisms places a greater demand on processing power when handling high-resolution pictures. Consequently, future research priorities will be on efficiently lowering the computational complexity and resource usage of the method without compromising or improving detection accuracy. Moreover, this paper's suggested modifications mostly focus on improving the accuracy of the model's predictions, leaving unexplored the possibility of improving the model's real-time responsiveness. The only static images in the training dataset at this time are two-dimensional ones, which is different from the dynamic visual information found in real-world application situations. Thus, future research must immediately focus on improving the algorithm's real-time performance optimization. Concurrently, in order to make sure that the model can better respond to the real-time decision-making requirements in real-world autonomous driving scenarios, video sequences or continuous dynamic picture data must be added for training.

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Sky Pixel Detection in Outdoor Urban Scenes: U-Net with Transfer Learning

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***Abstract*—The sky depicts a high visual importance in outdoor scenes, often appearing in video sequences and photos. Sky information is crucial for accurate sky detection in several computer vision applications, such as scene understanding, navigation, surveillance, and weather forecasting. The difficulty of detecting is clarified by variations in the sky's size, weather and lighting conditions, and the sky's reflection on other objects. This article presents a new contribution to address the challenges facing sky detection. A unique dataset was built that includes scenes of distinct lighting and atmospheric phenomena. Additionally, a modified U-Net architecture was proposed with pre-trained models as encoder VGG19, EfficientNetB4, InceptionV3, and DenseNet121 for sky detection to solve outdoor image limitations and evaluate the influence of different encoders when integrated with the U-Net, aiming to identify which encoder describes features of the sky accurately. The proposed approach shows encouraging results; as it presents improved performance over the adjusted U-Net architecture with inceptionv3 on the proposed dataset, achieving mean Intersection over union, dice similarity coefficient, recall, precision, and accuracy of 98.57 %, 99.57 %, 99.41 %, 99.73%, and 99.40 %, respectively. At the same time, the best loss was achieved in U-Net with VGG19 equivalent of 0.09.**

Keywords*—*Computer vision; transfer learning; semantic segmentation; sky detection; U-Net; machine learning

I. Introduction

Sky has received remarkable interest over the past few years as a robust indicator of outdoor scenes. The scene’s environmental information the sky provides is more significant than other scenes’ components. Therefore, sky detection is considered a crucial preprocessing step in various vision applications, such as weather classification [1], image or video editing [2], and navigation [3]. Moreover, the sky mask can be used to evolve the accuracy of object detection and tracking algorithms. Given its significance, sky detection research became one of the active topics in the computer vision field. This segmentation task is dedicated to identifying and isolating the sky region within a scene from other objects. However, the complexity of sky regions poses a significant challenge, owing to the vast range of pixel intensities and the notable variations in sky tone across different weather conditions and times of day. Semantic segmentation techniques represent the ideal solution for this task.

Semantic segmentation is one of the leading computer vision tasks where the object boundaries are delineated precisely. Segmentation tasks usually need complex, advanced techniques and high-quality data.

In addressing these challenges, semantic segmentation techniques have emerged as the preferred solution for accurate sky detection. By employing advanced algorithms capable of understanding the semantic meaning of image pixels.

The research community proposed two different approaches to solve the problem of sky segmentation. The first approach was the traditional approach where researchers tend to use certain methods like color-based, edge-based and region-growing.

Another approach is the usage of Machine learning. In this approach, some researchers tended to use traditional machine learning models e.g., Support vector Machine (SVM), K-means, and Logistic regression (LR). Others used more advanced techniques such as Deep learning (DL), e.g., CNN. More details about these methods will be discussed in the literature review section.

The article is arranged as follows: Section II is literature review Section III details the proposed method and dataset followed by preprocessing; Section IV explain network architecture. Section V discusses the experimental results, Section VI is discussion and finally, the paper concludes in Section VII.

II. Literature Review

Two main approaches for semantic segmentation techniques are used in sky detection tasks: the traditional-based approach and the deep learning-based approach. Firstly, traditional methods, such as edge, colour, and region-based techniques, have been introduced [4]. These traditional-based methods mainly rely on manually engineered features, such as color, texture, edges, or shape information, to identify the objects in images. The traditional methods are simple, fast, and computationally effective; however, their dependency on low-level hand-crafted features leads to low segmentation performance. On the other hand, deep learning-based methods such as U-Net [5], FCN[6], or Mask R-CNN [7] are considered end-to-end techniques [8]. These methods utilize the convolutional neural network (CNN) to extract features automatically. Although deep learning techniques need powerful hardware and extensive data, they are more robust to noise originating in sky regions from weather variations.

In the past few years, extensive research has been focused on sky and ground segmentation. Yehu Shen and Qicong Wang [9] proposed a technique based on gradient information to detect the horizon line. This method defined the border point in each column all over the image and then defined the region above these border points as the sky region. The previous method didn't detect the sky regions occluded by foreground objects. Zhao Zhijie et al. handled this challenge [10] by using color and gradient features to detect multiple border points in each column. The horizon-based approaches lost their detection efficacy as the complexity of scenes increased. Subsequently, classification-based approaches were introduced where the classifiers depend on the handcrafted features to detect the sky. Xiuzhuang Zhou et al. [11] proposed a novel technique that combines the advantages of superpixels and context inference. This method used features like lines, texture, color, position, and shape to train a Support Vector Machine (SVM) as a local superpixel classifier. Then, the conditional random field (CRF) was implemented as a contextual inference model to refine the segmentation. Additionally, Fl´avia de Mattos et al. [12] utilized eleven whiteness indexes as extracted features to feed (SVM) classifier. Yingchao Song et al. [13] proposed a novel model with two imbalanced SVM classifiers trained on several haze-relevant features. This model was trained on a hazy sky dataset with 500 annotated hazy images and divided the image into three areas: high confidence of being the sky regions with high confidence of not being the sky, and uncertain regions. In addition to the supervised traditional approach, cluster-based methods can be used in sky segmentation. Chao Fang et al. [14] deploy the K-mean clustering method to segment the sky regions based on pixels' brightness. Additionally, Yin et al. presented an innovative method called Sky-GVINS for achieving precise positioning in densely built environments and open sky areas with GNSS measurements [15]. This method relied on a lightweight sky segmentation, utilizing a global threshold technique to distinguish sky and non-sky regions in fish-eye sky-pointing imagery. The experimental dataset comprised 500 images representing diverse conditions, such as occlusions in the sky presented by buildings and trees.

Traditional machine learning techniques based on hand-crafted features adapted poorly to the variational complex sky appearance. Therefore, computer vision scientists have directed their attention to end-to-end deep learning techniques that extract features automatically using CNN to handle sky segmentation tasks. Yi-Hsuan Tsa [16] proposed a sky segmentation model based on FCN. This model was trained on 15,000 images from the LMSun dataset and achieved 94 %-pixel accuracy. Radu P. Mihail et al. [17] created a new dataset called Sky Finder and evaluated three approaches for sky segmentation in natural outdoor scenes. The results argued poor performance due to local lighting and weather conditions. Then, a new deep ensemble method that combined the output of existing methods with raw image data using rCNN was proposed and shown to improve performance with an MCR of 12.96%. Zou et al.'s study presented a novel approach to sky segmentation, combining computer vision and deep learning [18]. They proposed a new computer vision-based "flow propagation" method for robust background motion and feature estimation. These features were fed into a customized deep CNN model ResNet-50 based for training. The networks can be effectively trained on videos without using external data annotations. The proposed method was tested on BDD100k datasets. This innovative blend of handcrafted and CNN features demonstrates a unique strategy in sky segmentation research. The method is designed to operate on trained data; therefore, it does not work on different datasets. Wang et al. introduced a real-time sky segmentation method formulated for mobile augmented reality based on a deep semantic network called FSNet [19]. The authors designed the method for efficient segmentation under varied weather conditions, validated through extensive testing on a substantially large dataset. For refining the segmented regions, sky-aware constraints were included, which considered factors such as color, the sky's position, and temporal coherence across neighbouring frames. Extensive qualitative and quantitative analysis testing demonstrated that the proposed method surpasses other leading methods in real-time performance. The result's accuracy was gauged using the mean intersection over union (mIOU) metric, achieving 90.17%. However, the method showed limitations and did not perform efficiently for heterogeneous skies, such as during sunsets. Recently, U-Net has been one of the most commonly developed deep learning algorithms, especially for biomedical segmentation tasks. Due to its efficiency, U-Net architecture was widely implemented in all segmentation applications, including sky segmentation. Liba and colleagues introduced a precise method for sky optimization aimed at enhancing the sky's appearance in images, including sky segmentation [20]. They constructed a dataset of sky masks utilizing partially annotated images that were painted and refined using a modified weighted guided filter. Moreover, they trained a U-net neural network to conduct sky segmentation on RGB images by predicting the sky probability for each pixel. The Morph-Net method was employed to optimize performance and minimize network size. In their work, Kuang et al. proposed an innovative framework for segmenting sky and ground in the visual navigation of planetary rovers [21]. The study introduced a U-shaped neural network entitled NI-U-Net and incorporated a conservative annotation method to minimize human interference. Augmented results were exhibited through a pre-training process across complex scenarios using the Skyfinder dataset, a well-acknowledged benchmark. The framework was evaluated based on seven metrics, achieving high results.

Although deep learning-based segmentation models such as U-Net have achieved high performance, the requirement of huge high-quality labelled data and large costly computation power for model training limit their implementation in practical systems. Training CNN-based models from scratch is an impractical time-consuming technique as it takes a long time for the model to converge. The transfer learning approach was introduced as an ideal solution to overcome these challenges where the model uses prior information in a new task. The pre-trained weights learned from tasks that are not completely relevant to new tasks are more useful than randomly initialized weights.

In this work, the main objective is to remarkably enhance the sky segmentation task in adverse weather and lighting conditions by a modified U-Net architecture with pre-trained models as encoder VGG19, EfficientNetB4, InceptionV3, and DenseNet121 for sky detection to solve outdoor image limitations and evaluate the influence of different encoders when integrated with the U-Net, aiming to identify which encoder describes features of the sky accurately. The reason behind choosing the U-Net architecture is that it outperformed other architectures used in most of the research works. The integration between UNet architecture and transfer learning allows us to handle sky segmentation tasks effectively with high segmenting performance while saving computation power.

III. Proposed Methodology

The goal in this proposed approach is to simplify image segmentation and develop efficient, robust algorithms for sky segmentation. The methodology showed in Fig. 1. forms the basis of our approach, ensuring that the outcomes are trustworthy and valid. The widely used U-Net architecture was modified by adapting different backbones as an encoder path, which improved the depth of the network and produced better results. The model was tested using collected dataset and found that our approach outperformed existing methods in terms of capabilities. The overall approach is given in Fig. 1.

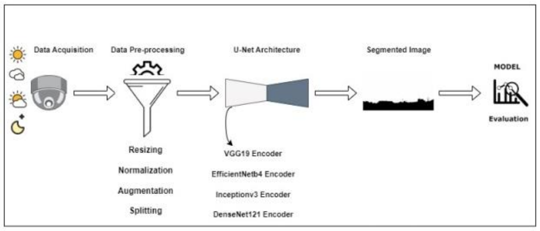

Fig. 1. Proposed methodology.

A. DataSet Acquisition

Data was systematically collected to capture different aspects of the sky. This data was collected at various times and in diverse weather conditions. To ensure comprehensive collection, stationary outdoor cameras were strategically placed in 11 specific urban locations in the Kingdom of Saudi Arabia. These regions were chosen based on their varied urban landscapes, allowing for expansive sky views to be captured.

The dataset incorporates different periods of the day (morning, midday, and evening) as well as various weather conditions (sunny, cloudy, partly cloudy). This comprehensive dataset allows for a wider range of image variations. In this research work, special care was taken to ensure that the photos collected were high quality and free from any unwanted elements or issues such as artifacts, noise, repeated images, or spots on the lens. The resulting dataset consists of RGB images that brightly represent the dynamic nature of the sky in these areas. In total, the dataset consists of 1691 diverse images captured. It's important to note that all images in the dataset contain both sky and non-sky areas. Sample images from each location are presented in Fig. 2.

B. Ground Truth

To enhance the accuracy of the dataset even further, a specialized computer vision annotation tool called CVAT was utilized. Manual annotations were made for each image through this tool by creating binary mask segmentations. These masks specifically separate regions into two categories: sky and non-sky. The definition of "sky" includes sky and other elements commonly found in skies, like clouds, sun, or moon. Conversely, "non-sky" consists of all other areas that do not fall under this sky category. These masks are ground truth.

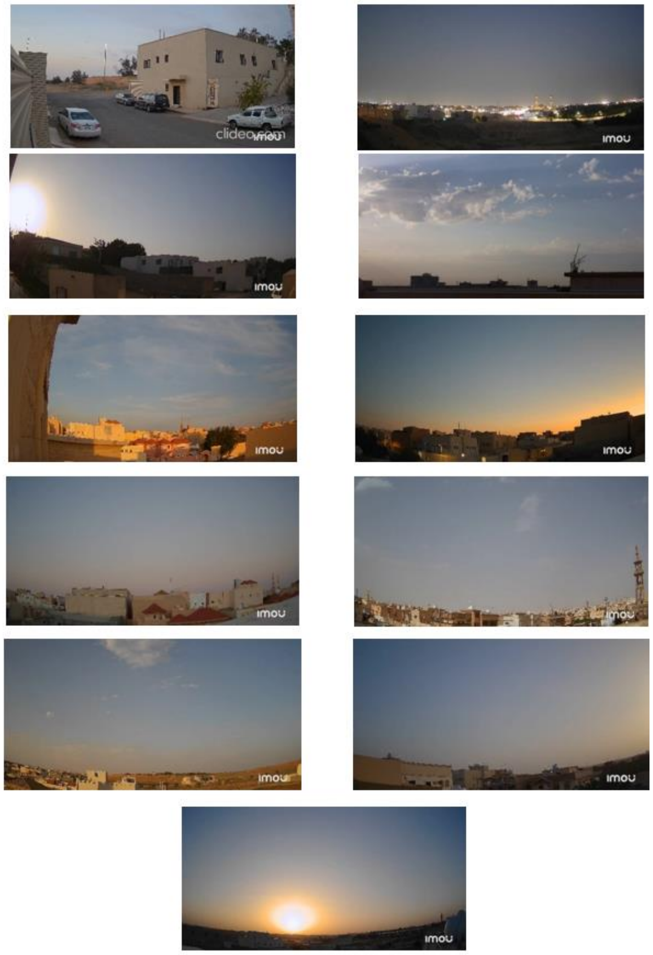

Fig. 2. Sample images from different locations.

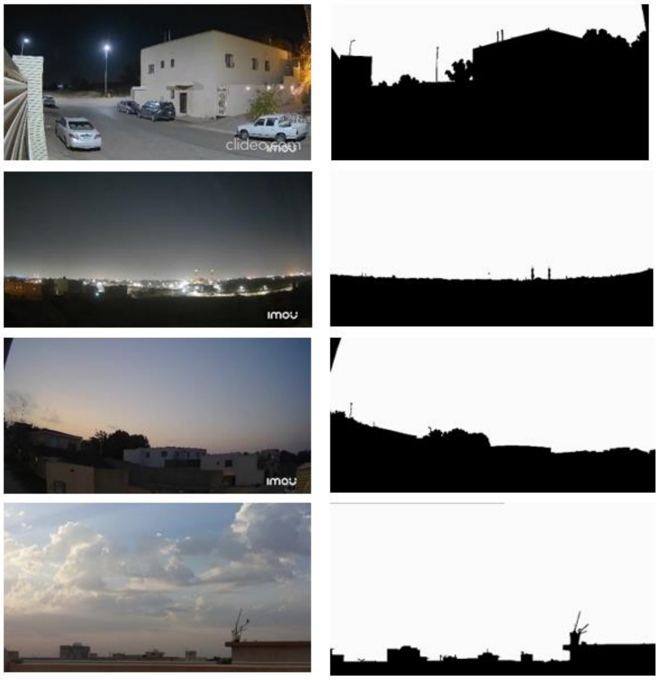

Fig. 3. Some of the data samples with ground truth.

Ground truth masks are an essential element for any machine learning application. They provide an essential reference or benchmark for algorithm training in image processing tasks, hence the term 'ground truth' [22], as they provide a standard against which the outcomes of the algorithms can be measured. Ground truth masks were generated for each image. These are binary masks, where 0 represents the sky region, and 1 represents the non-sky regions. Fig. 3 provides samples from dataset and their corresponding ground truth masks.

C. Data Preprocessing

Data pre-processing was carried out to increase computational performance and have efficient processing. First, the images were resized to 256×256 pixels. Additionally, the data normalization was also carried out by normalizing each pixel value of the data. By dividing each pixel value by 255, all data values fall within a range from 0 to 1. This normalization process is beneficial as it improves both the speed and accuracy of convergence during further calculations. Furthermore, masks (which indicate specific areas) were converted into binary format for more accessible analysis and understanding. To ensure accurate and reliable results, the images in the dataset were carefully divided into two separate datasets: the training dataset and the validation dataset. The training dataset accounts for 80% of collected data, while the remaining 20% is allocated to the validation dataset, allowing the algorithm to familiarize itself with various patterns and features within the images.

To address the issue of insufficient data and overcome hardware constraints, a solution was implemented using the ‘ImageDataGenerator’ class from the Keras framework, augmented images were generated on the fly during each epoch of training. This ensured that the model received diverse new variations in each iteration, effectively enhancing its ability to learn and generalize patterns. This strategy helps mitigate overfitting issues that often arise when working with small datasets. The augmentation techniques for this research include random rotation, horizontal and vertical shifts, shear transformation, and zoom. Fig. 4 presents a selection of samples that demonstrate the effects of these augmentation techniques on images in dataset.

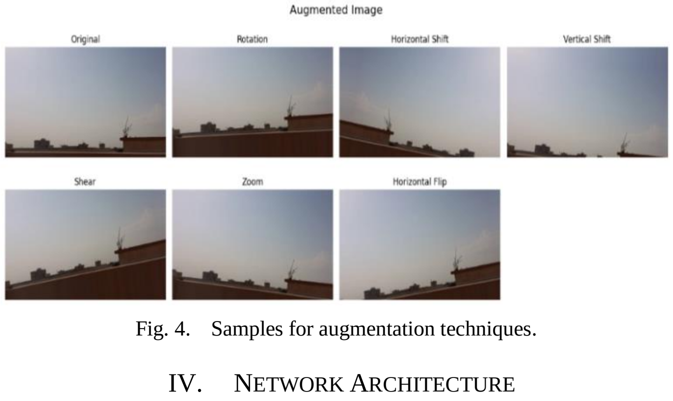

Fig. 4. Samples for augmentation techniques.

IV. Network Architecture

The illustration in Fig. 5 demonstrates the working of the proposed architecture for an RGB input image with dimensions 256×256×3. The segmented output map with dimensions 256×256×1 using the U-Net [5] network is received at the output. It is observed that there is no reduction in size between the input and output.

Four different deep learning-based networks are proposed as alternatives to the contracting path for the U-Net. These encoders are VGG19 [23], EfficientNetb4 [24], InceptionV3 [25], and DenseNet121 [26] to extract deep features, both height and width progressively decreasing while channel numbers increase. This channel augmentation enables capturing higher-level features as information flows through this pathway. The model undergoes a final convolution operation at the bottleneck, resulting in a feature map of size 16×16×1024. The expansive path then reconstructs an image of the exact dimensions as the original input from this feature map. Up-sampling layers are employed to increase spatial resolution while reducing channel count. The decoder layers utilize skip connections from the contracting path to locate and enhance features in the image. Ultimately, each pixel in the output image represents a label corresponding to the class in the input image. In this case, the output is a segmentation map, distinguishing between foreground and background regions for each pixel. The foreground represents the sky region, and the background represents the non-sky regions.

The crucial hyperparameters necessary for the convergence of the proposed models were identified. This includes batch size was set to 32 for all models, 100 epochs, AdamW optimizer selection, and learning rates set to 0.00001. The loss function applies the binary cross-entropy.

The framework for statistically evaluating the efficacy of the models for sky segmentation is one of the key points of emphasis in the research. A suite of metrics is selected to quantify the performance of the models. The work leverages mean Intersection over Union (mIoU), Dice Similarity Coefficient (DSC), precision, recall, and accuracy, as critical metrics for this study.

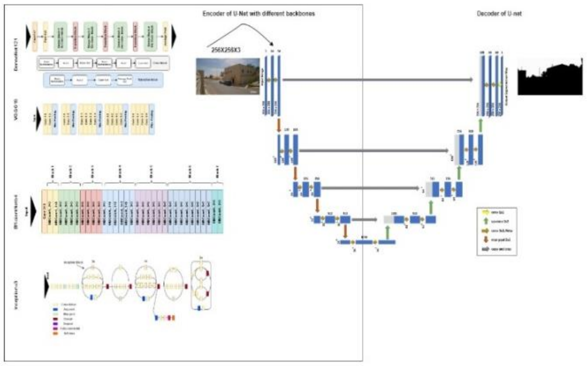

Fig. 5. Demonstratration of the working of the proposed architecture.

V. Results

The operating system of this work is Windows 11, the deep learning environment is Keras and TensorFlow, and the programming language is Python. The hardware configuration is an Intel Core i7-2.80 GHz CPU and 16.0 GB RAM.

In this research study, the proposed novel deep learning algorithm for sky segmentation was evaluated by utilizing various encoders within the U-Net architecture and subjecting it to critical analysis.

After several experiments, models that consist of the encoder employing VGG19, EfficientNetB4, InceptionV3, and DenseNet121 were compared, InceptionV3 U-Net showed the best performence, obtaining remarkable mIOU and DSC scores as high as 98.57% and 99.57% respectively. mIOU stands for mean Intersection over Union while DSC stands for Dice Similarity Coefficient which tells us how great the proposed model can perfectly draw the Sky region in the images. Such high scores are indicative of the model's robust performance in capturing the intricate details of the sky, laying the foundation for applications such as obstacle detection and path planning for autonomous vehicles.

Table I depicts the model’s performance concisely, measuring the Recall, precision, accuracy, and F1 score. Embodied in the table is not only the performance of the Inceptionv3 U-Net but also its other architectures, the VGG19 U-Net, the DenseNet121 U-Net, and the Efficientnetb4 U-Net. Though the VGG19 U-Net, the DenseNet121 U-Net, and the Efficientnetb4 U-Net all offer comparable results, their scores are slightly less in comparison to the Inceptionv3 U-Net. The high performance that is demonstrated by all models serves as a testament to the ability of different encoders to amplify the U-Net architecture where sky segmentation is concerned.

TABLE I. PERFORMANCE EVALUATION FOR SKY SEGMENTATION MODELS

Evaluation	**Models**			
	VGG19 U-Net	***Densenet121 U-Net***	***Efficientnetb4 U-Net***	***Inceptionv3 U-Net***
mIoU	98.46 %	98.48 %	98.45 %	98.57 %
DSC	99.53 %	99.54 %	99.53 %	99.57 %
Recall	99.36 %	99.73 %	99.33 %	99.41 %
Precision	99.71 %	99.35 %	99.72 %	99.73 %
Accuracy	99.35 %	99.36 %	99.34 %	99.40 %
Loss	0.09	0.11	0.14	0.11

A further illustration of training and testing curves is shown in Fig. 6 and Fig. 7. In Fig. 6, the upper row corresponds to the InceptionV3 U-Net model, revealing its superior performance compared to the lower row representing the DenseNet121 U-Net model. Similarly, Fig. 7 presents the learning trajectories of the VGG19 U-Net and EfficientNetB4 U-Net models, offering nuanced perspectives on their adaptability and convergence. The models have performed consistently well over both the training and validation sets, hence no signs of overfitting. In addition to the numerical metrics, it can be seen that the loss value during training is consistently low, again reaffirming the robustness of training procedures. Moreover, it can be concluded the models with high accuracy scores can do pixel classification in the sky region very well, which indicates the models are good enough even in discerning subtle details.

The attainment of high learning due to the decrease in loss curves indicates the learning models’ saturation. Conversely, the rise in accuracy and IOU curves shows that the model is still learning, which means that the learning phase is not over. Both curves are proposed to be well-balanced so as to enable the learning process to be terminated.

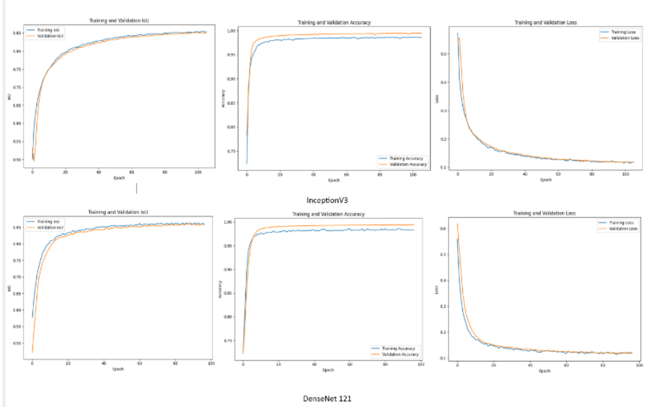

Fig. 6. The performance curves of the inceptionv3 U-Net and Densenet121 U-Net.

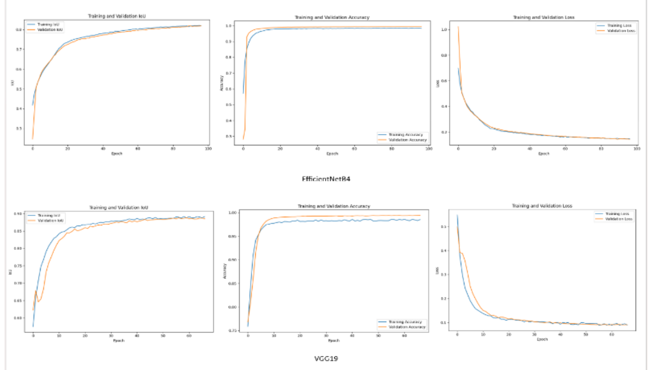

Fig. 7. The performance curves of the Efficientnetb4 UNet and VGG19 Unet.

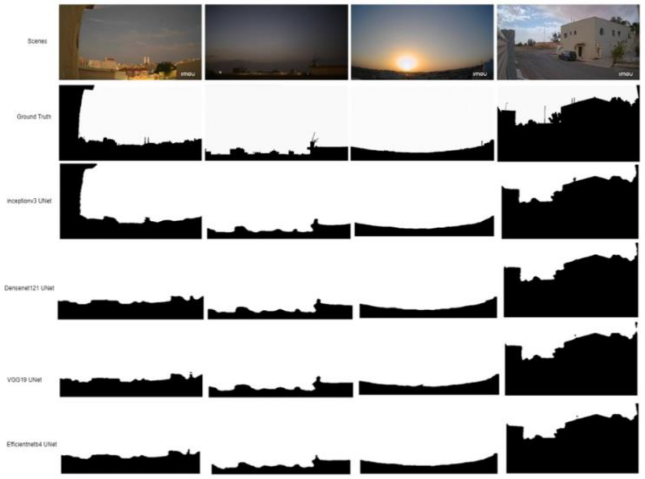

Fig. 8. Samples of prediction of the models.

The qualitative assessment of model predictions is presented next in Fig. 8. This includes visual samples of the models’ predictions on various scenes in different weather conditions and times of the day. The examples show that the models perform well in challenging setups such as back illumination or low light. This preliminary qualification holds true across the U-Net architecture and for the different backbone encoders, where it is evident that all models very accurately detect sky and ground pixels in various scenes.

VI. Discussion

The proposed models are able to perform with a relatively high degree of accuracy. In particularly hard scenarios, such as night scenes, the results are outstanding. They have done quite well in the task of distinguishing sky- and non-sky regions. And have done much better than other systems to avoid misclassifications such as white buildings as clouds, with a significantly greater precision.

However, the models' limitations become apparent in more complex scenarios, such as scenes with intricate structures like trees or poles on buildings. In these instances, the models struggle to accurately detect sky areas, revealing areas that might benefit from further refinement. This acknowledgement of limitations is crucial for guiding future iterations of the models.

This project opens avenues for future research, outlining potential directions to enhance the model's capabilities and address identified limitations. As a future work, various complex sites will be incorporated to train models robustly in the future by increasing dataset used in this project. Additionally, assessing how the model performs on different datasets to assess its adaptability to different scenarios and datasets. Moreover, this study will be expanded by focusing on a specific challenge, e.g., in weather phenomena, such as dust or rain and how to detect the sky.

VII. Conclusion

The finalization of this work throws light on the significant achievements that have been made in the field of Semantic Sky Segmentation. Initially, the main aim was to search for the most suitable encoder that could capture all the details of the sky, ideally during the segmentation process, to get very accurate results. The whole project was carried out in a series of different stages where alterations were made to the U-Net Architectures that employed several other encoders such as VGG19, EfficientNetB4, InceptionV3, and DenseNet121. The end-to-end binary segmentation model was a key stage in the proposed approach. The project's foundation rested on various steps, from comprehensive data preparation to the advanced image processing steps. The choice of the Keras framework facilitated a simplified model construction process, allowing for essential data augmentation to increase the dataset and enhance the model's overall performance.

Model evaluation was accomplished with the help of metrics like mIOU, Accuracy, Precision, Recall, DSC, Loss, etc. The results were as follows: the mean Intersection over Union, Dice similarity coefficient, recall, precision, and accuracy scores of 98.57%, 99.57%, 99.41%, 99.73%, and 99.40%, respectively. Additionally, it's noteworthy that the U-Net with VGG19 equivalent achieved the best loss of 0.09, underscoring its effectiveness in minimizing error.

This comprehensive approach of the evaluation process helps to understand the various aspects of the models. The InceptionV3 UNet model was identified as the most robust performer among the models tested over this dataset. Thus, the extended view of performance metrics for the different models validated the precision of the model's segmentation.

The success of this project lies not only in the numbers but the proof lies in models' improved perception of complex scenes and their ability to work more effectively with applications. These have done well with an ability to tell sky pixels away from the ground.

In conclusion, the outcomes of these experiments not only contribute to the growing body of knowledge in computer vision but also pave the way for practical applications where precise sky segmentation holds significant importance.

Acknowledgment

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Revolutionizing Plant Disease Detection in Leaves: An Innovative Hybrid ABOCNN Framework for Advanced and Accurate Identification

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Abstract—**Plant diseases are a persistent threat to the global agricultural economy, compromising food supply and security. Accurate and early diagnosis is vital for effective agricultural management. This study addresses this gap by introducing a better approach for identifying plant diseases in leaves: the Integrated Hybrid Attention-Based One-Class Neural Network (ABOCNN) System. The system uses deep learning and domain-specific information, as well as powerful neural networks and attention processes, to extract features unique to a certain ailment while excluding irrelevant data. By dynamically focusing on prominent areas in leaf images, the proposed methodology obtains an impressive 99.6% accuracy, beating both traditional approaches and cutting-edge deep-learning approaches by an average of 12.7%. The practical use of this strategy has a significant influence on crop yield and agricultural sustainability. Attention maps increase interpretability and help individuals comprehend more fully how decisions are made. The system, written in Python, is precise, scalable, and adaptable, making it a helpful tool for a wide range of agricultural applications combining multiple plant species and disease classifications. With an incredible 99.6% accuracy rate, the Integrated Hybrid ABOCNN Technology provides an innovative method for diagnosing plant diseases, outperforming conventional approaches by 12.7%. Attention maps increase interpretability and give important information about the model's decision-making processes.**

***Keywords*—Convolutional Neural Network (CNN); attention model; leaf disease detection; attention-based one-class neural network; crop production**

I. Introduction

Plant leaf detection refers to the process of identifying and analyzing the characteristics of leaves in plants. Leaves are vital components of plants, playing a crucial role in photosynthesis, respiration, and transpiration. By detecting and understanding various leaf attributes, such as shape, size, color, and texture, researchers, botanists, and agriculturalists can gain valuable insights into plant species identification, health assessment, disease detection, and growth monitoring. Leaf detection has traditionally been a manual and time-consuming task, requiring experts to visually inspect and classify leaves based on their features [1]. However, automatic leaf recognition is now more practical and precise because to developments in neural networks, algorithmic learning, and computational imaging methods. By utilizing sophisticated algorithms and neural networks, leaf detection systems can analyze digital images or live video feeds to identify and segment leaf regions from complex backgrounds. These systems can also extract relevant features from the detected leaves, enabling further analysis and classification [2]. The applications of plant leaf detection are diverse and impactful. In agriculture, leaf detection can aid in crop management, enabling early detection of diseases, nutrient deficiencies, or pest attacks. It can assist in optimizing irrigation, fertilization, and overall plant health monitoring. Additionally, leaf detection has significant implications in environmental conservation, as it can aid in species identification, biodiversity assessment, and ecosystem monitoring [3]. Overall, plant leaf detection offers an efficient means to study and understand the characteristics of leaves, providing valuable insights into plant health, growth, and species identification. With continued advancements in technology, this field holds great potential for revolutionizing plant science, agriculture, and ecological research [4].

A cutting-edge method for automatically identifying and detecting leaves from plants is foliage identification using deep learning, which makes use of the capabilities of networks. Deep learning models, especially CNN, have demonstrated outstanding ability in image analysis and identification, which makes them suitable for jobs requiring the detection of leaves. In order to distinguish leaf in the foreground and correctly identify their existence in an image, the subject learns to identify patterns, characteristics, and architectures that are exclusive to leaves. Intricate nuances and changes in leaf attributes, like as form, texture, venation patterns, and color, may be captured by deep learning models since they are excellent at autonomously generating hierarchical representations of data. They can handle complicated leaf shapes and identify between many plant species quite effectively [5]. The key benefit of leaf identification using deep learning is its ability to generalize well to unseen data. Once trained, the model can efficiently process new leaf images and accurately identify leaves even in diverse environments and under varying lighting conditions. The applications of deep learning-based leaf detection are vast. It can assist botanists and researchers in plant species identification, enabling quick and reliable classification of leaves. It also plays a crucial role in plant disease diagnosis and monitoring, as the detection of abnormal leaf patterns or discoloration can indicate potential health issues [6]. Additionally, deep learning-based leaf detection contributes to precision agriculture by enabling automated crop monitoring, yield estimation, and targeted interventions for optimizing plant health and growth. However, it's important to note that deep learning-based leaf detection requires a large and diverse dataset for training the model effectively. The initial training dataset's reliability and accurate representation have an important effect on the model's accuracy and generalizability. Plant leaf diseases represent a severe threat to crop production, efficiency in agriculture, and the availability of food [7]. These illnesses need to be correctly recognized and categorized early on in order to receive quick therapies and effective management techniques. Due to their shown high effectiveness in image recognition tasks, algorithms that utilize deep learning are especially well-suited for the diagnosis and classification of diseases of plant leaves. A sophisticated hybrid approach called ABOCNN has been created in this situation, fusing the benefits of several deep learning architectures [8].

The ABOCNN framework integrates the power of CNN and attention-based mechanisms to enhance disease detection and classification accuracy. CNNs are recognized for their capacity to autonomously acquire and extract significant characteristics from images. Attention mechanisms concentrate on critical regions, allowing the network to give better consideration to disease-specific patterns in leaf images [9]. The key advantage of the ABOCNN framework lies in its ability to handle complex and diverse disease patterns, including subtle variations in leaf textures, discoloration, lesions, and other disease-related characteristics. By integrating CNNs' feature extraction capacities with attention processes, the framework may efficiently collect both global and local disease-related information, permitting precise and accurate plant leaf disease diagnosis [10]. The suggested paradigm has important effects on crop management, farming, and the pathology of plants. It provides a quick and automated method for identifying and categorizing plant leaf diseases, enabling early intervention with targeted therapies. In turn, this aids agronomists and farmers in making educated choices, allocating resources efficiently, and reducing crop losses. In conclusion, the ABOCNN framework provides a cutting-edge method for the identification and categorization of plant leaves using deep learning. It improves the dependability and precision of disease identification by merging CNNs and attention processes, which helps to create more efficient and environmentally friendly agricultural practices [11].

The key contributions of this paper are as follows:

- With a sophisticated hybrid ABOCNN architecture as the foundation, the study introduces a revolutionary deep learning technique that results in a significant increase in accuracy.
- The Attention Mechanism enhances the capacity of the model to identify disease-specific characteristics in leaf images. The method enhances accuracy and making decisions by constantly attributing significance to geographical elements.
- Attention maps enhance the comprehensibility of the suggested method. These maps provide users with useful knowledge into the procedure and enable them to better understand the procedure for making decisions.
- The hybrid ABOCNN model is adaptable and scalable, making it suitable for usage with a wide range of plant species and diseases. Because of its adaptability, it may be employed in a variety of agricultural applications.
- The finding signifies a substantial advancement in the treatment of agricultural conditions using deep learning. The hybrid ABOCNN approach has the capability to significantly enhance agricultural results by transforming plant disease detection and intervention techniques.

The approached paper's manuscript is structured as follows: Several similar works are reviewed in Section II. Information on the problem statement is given in Section III. The planned ABO-CNN is detailed in depth in Section IV. In Section V, research findings are shown, reviewed, and a thorough assessment of the suggested strategy in comparison to current standards is presented. The paper's conclusion is presented in Section VI.

II. Related Works

Lu et al. [12] proposed utilizing a CNN to classify disease of plant leaf. They examined the most recent CNN networks that were relevant to classifying plant leaf diseases in their article. Additionally, they outlined the DL concepts involved in classifying plant diseases and provided the CNN methodologies used in the process. Additionally, it summarized various issues with the DL utilized for classifying plant diseases based on extrinsic and intrinsic characteristics, as well as the accompanying remedies. Inadequate datasets in terms of number and variety are the main issue with CNN-based DL's application to the categorization of plant diseases. This condition contributes to some extent to all the other issues that have been raised. The practical application is significantly influenced by adequate datasets. However, external factors like seasonality and climate may readily alter data collection, and image labelling is often a time-consuming and hard operation. These elements make it very challenging to create an effective dataset.

Sen et al. [13] proposed classifying leaf disease using the EfficientNet network. Considering the reality that the raw image size had to be restricted due to hardware constraints, the EfficientNet architecture provided superior outcomes than previous CNN algorithms that had been fed images as inputs with higher dimensions. When the initialization times of each model per session were looked at, AlexNet showed less overall accuracy and precision than the other models. It took 310 and 352 s in both the initial and augmented datasets, respectively. The dataset on plant leaf disease can be expanded, though. This will aid in the creation of models that can anticipate outcomes more accurately under challenging circumstances. Pathologists for plants and producers are going to be able to promptly identify diseases of plants and implement necessary precautions by utilizing these enhanced techniques in mobile situations.

Hassan et al. [14] suggested the use of transfer-learning and neural algorithms, researchers improved the identification of plant-leaf illnesses. They switched from standard suppression to depth-separable inversion in this study, which minimizes the amount of work of the computations. The models were trained on a dataset comprising 14 distinct species of plants, 38 different types of diseases, and healthy foliage from plants. Other parameters, such as the overall amount of sections, being abandoned, and the quantity of epochs, were used to evaluate the models' effectiveness. The created models fared better in terms of overall accuracy rates for sickness categorization than traditional handmade based on features methods. In comparison to earlier deep learning techniques models, the newly constructed model behaved more effectively while requiring less training time. The CNN-based deep learning techniques architecture has certain limitations even though it has excellent detection rates for identifying plant diseases. The disadvantages of them are that whenever there doesn't seem sufficient noise in the collection of photographs, the deep-learning model may be misclassified.

Zhou et al. [15] KNN Classifier is proposed for the proposed Color and Material Based Methodology for the Identification and Diagnosing the Leaf Disease. In the current study, the K-nearest neighbor classifier was recommended as a method for classifying and identifying leaf diseases. For categorization, the leaf disease images textural characteristics are retrieved. In this study, a KNN classifier will be used to categorize numerous plant species' illnesses. The suggested method has a 96.76% accuracy rate for correctly identifying and diagnosing the chosen illnesses. However, there are disadvantages and difficulties, including high computing costs, sluggish performance, memory and storage problems for huge datasets, sensitivity to metric selection and distance, and vulnerability to the plague of dimensionality.

Sibiya et al. [16] advocated the use of CNN in order to distinguish healthy leaves from leaves with illnesses on maize. To create a collection of networks for illness image recognition and classification, this study uses CNN aided principles. The CNN network was trained using Neuroph to identify and categorize images of the wheat diseases of the leaves that were gathered using a mobile device's camera and exercise. Three different forms of wheat leaf diseases could be distinguished by the created model from healthy leaves. This study focused on the ailments that cause the most harm to Southern Africa's maize crops, widespread rust and grey leaf spot. The calculation length and sensitivity to outliers of the procedure are both rather high.

Lv et al. [17] recommended using Feature Enrichment Based Maize Leaf Disease Detection and DMS-Robust Alexnet. They initially developed an architecture for leaf maize characteristic augmentation in order to improve the qualities of wheat in a complicated environment. Then, a special neural network called DMS-Robust Alexnet is developed. It is based on the core Alexnet architecture. The DMS-Robust Alexnet uses dilatation of conjunction and multiple scales conjunction to boost the effectiveness of feature extraction. proposed using DMS-Robust Alexnet and Feature Enhancement Based Wheat Leaf Disease Diagnosis. They initially built an infrastructure for leafy wheat characteristic augmentation to increase the attributes of wheat in a complicated environment. This DMS-Robust Alexnet, a one-of-a-kind neural network, is then developed. It is based on Alexnet's core framework. The DMS-Robust Alexnet improves feature extraction efficiency by utilizing multi-scale merging and synthesis dilation.

The literature review points out several shortcomings in the current methods of plant leaf disease classification, including the inability and difficulty of gathering sufficient data, hardware limitations, high computing costs, sensitivity of metric selection, and vulnerability to dimensionality constraints. These limitations make it more difficult to identify plant diseases accurately and effectively. The proposed solution uses an advanced hybrid ABOCNN deep learning strategy to tackle these problems. This method enables accurate disease diagnosis by dynamically focusing on relevant portions of leaf pictures using one-class neural networks and attention techniques. This strategy not only outperforms CNN-based and conventional methods in terms of operation, but it also enhances interpretability through attention maps, making it a viable substitute for improved agricultural outcomes. Feature Enrichment Based Maize Leaf Disease Identification with DMS-Robust Alexnet, CNN-based models, KNN Classifier, transfer learning, and Efficient Net are some of the approaches that have been assessed.

III. Problem Statement

The literature review, which emphasizes the major impact of diseases of plant leaves on agriculture and food security, serves as the foundation for the current study [18]. It is obvious that existing plant disease detection methodologies may not be able to deliver the level of accuracy and repeatability required for effective preventive and remedial interventions. This conclusion underscores the critical requirement for advances in plant disease detection systems, stimulating the development and research of a more precise and reliable techniques for dealing with the challenges these agricultural threats provide. The work intends to solve the identified challenges in plant disease diagnosis by developing a more complicated hybrid deep learning architecture and using a dependable strategy. The research aims to improve the capacity and understanding of the disease detection process while acknowledging the limitations of traditional approaches and CNN-based techniques in terms of consistency and accuracy. The goal is to increase disease detection efficacy by deleting unnecessary information and dynamically concentrating on disease-specific regions in plant leaf images utilizing one-class neural networks as well as attention procedures. This method attempts to advance disease detection approaches, resulting in more accurate and reliable outcomes in the natural setting of plant pathology [19].

IV. Proposed Advanced Hybrid ABOCNN Framework

The proposed methodology for revolutionizing plant disease detection in leaves, named the Hybrid ABOCNN Framework, comprises multiple stages and processes designed to enhance the accuracy and efficiency of identifying diseases in rice leaves. The dataset used consists of 5932 images of rice leaves with diseases like brown spot, bacterial blight, blast, and tungro, which were obtained from fields in western Odisha. These images underwent augmentation, increasing the number of images by six times. The pre-processing stage involves applying a Gaussian filter to remove noise and blur, followed by feature extraction using the CNN approach. The CNN is a complex network consisting of inversion, pooling, and fully connected layers, which are trained using the VGG-16 structure. The incorporation of the Attention Mechanism enhances the CNN's performance by assigning weights to important spatial features, thereby improving disease detection and classification accuracy. The proposed Attention-CNN model combines the benefits of both CNN and the Attention Mechanism. Training is performed using the Adam optimization method with cross-entropy as the loss function. The overall methodology, from data collection and pre-processing to feature extraction and classification, aims to create a robust and accurate framework for identifying plant diseases in rice leaves, ultimately contributing to more efficient agricultural practices. Fig. 1 shows the proposed ABOCNN framework.

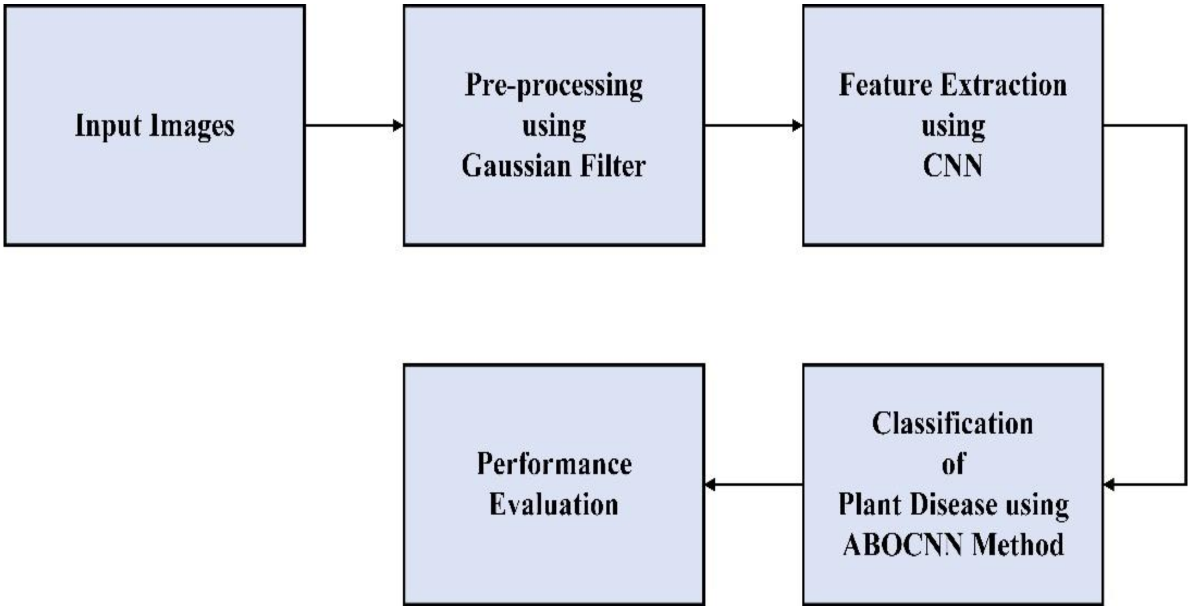
Input Images
Pre-processing using Gaussian Filter
Feature Extraction using CNN
Classification of Plant Disease using ABOCNN Method
Performance Evaluation

Fig. 1. Proposed hybrid ABOCNN framework.

A. Dataset

The collection comprises 5932 images of leaves of rice with diseases such as brown spot, bacterial blight blast, and tungro. The original images were taken using an exceptional grade of several fields of rice in western Odisha. The diseased areas in patches were obtained from the large original images. The patches were subsequently processed as samples of data after being converted to 300 300 pixels. Out of the 800 total images in the initial collection, 200 images from every group were picked for testing. The remaining 5132 images were augmented using the collection. Simple rotation and flipping operations were conducted to all photographs as part of the augmentation process, including revolve left 90 degrees, revolve right 90 degrees, flip vertically, flip horizontally and rotate 180 degrees. Consequently, including the upgraded images, the overall amount of images increased by six times. The more improved photographs there are, the more likely it will be that the camera system will pick up the proper qualities. Table I contains a list of the experiment's images by name and number. The data sample are allocated at randomly in amounts of 80:20 for both validation and training. Evaluation along with training samples are randomly selected for each execution [20].

TABLE I. TRAINING AND VALIDATION OF THE DATA SAMPLES

Leaf disease	Number of images used of augmentation	Number of original images	Number of images used for Training and validation	Number of images used for Testing
Bacterial Blight	1384	1584	8304	200
Tungro	1108	1308	6648	200
Brown Blast	1400	1600	8400	200
Blast	1240	1440	7440	200
Total	5132	5932	30,792	800

B. Pre-processing using Gaussian Filter

The process of separating features necessitates the transformation of unorganized information into quantitative qualities in order to capture and keep the specifics of the very beginning of data. Each patient processes information in a different way, and these traits are determined from the entire set of representations that were collected. To identify, the number of dimensions associated with the representation must be reduced, whereas the overall size of the representation increases throughout testing. In order to remedy this problem, features are removed. The GLCM is utilized during the feature extraction procedure. By producing several sets of images with specific values, it shows the graphical representation's structure of hierarchy. The GLCM displays the intensity of the displayed pixels by using the appropriate grayscale. The quantity of energy, comparison, connection, entropy, homogeneity, and other properties of the second-degree representation are evaluated in order to eliminate the statistically significant texturing feature. The first stage is image pre-processing. A Gaussian filter with a smoothed method is applied to the leaf during the pre-processing stage to minimize noise and eliminate blur from the image to increase the enhancement of the leaf image. The representation of this filter is defined in Eq. (1),

$$G(u,v) = \frac{1}{2\pi}(\varphi^2)\left(e^{-\left(\frac{u^2+v^2}{2e^2}\right)}\right) \tag{1}$$

Intensity gradient of the image is found out as given below in Eq. (2)

$$N(v,v) = \sqrt{g_u^2(u,v) + } g_v^2(u,v) \tag{2}$$

Edge thinning occurs when the gradient's degree is determined based on the strength of the edges. To eliminate the visible edge pixels caused by noise in the image, edge pixels with inadequate gradient values are deleted, while those with large gradient values are retained. a technique for computing texture and color information simultaneously. The texture of leaf images is often inconsistent, making it difficult to recognize textural patterns. Furthermore, typical techniques lose chromatic information, preventing them from supplying the key texture feature. In this study, we offer a novel technique in which the input image is completely enclosed by a circular window that travels over it [21].

The coordinates of the point (x, y) is home to the shade vector of characteristics (u, v). The supplied dimensions for (u, v) are (q cos t, q sin t), where u is equal to q cos θ and v is equal to q sin θ. The location of the starting point of these orientations is the circular window's centroid. The t(r) represents the color-texture translation of the provided two-dimensional images D (u, v) at r radius. This may be calculated through calculating the mean of D (q cos θ, q sin θ) within a particular region of r. It is expressing itself as Eq. (3):

$$t(r) = \frac{1}{2\pi r}\int_0^{2\pi} D(qcos\theta, qsin\theta)d\theta \tag{3}$$

C. Feature Extraction Using CNN

CNN are an appropriate strategic option for feature extraction in such circumstances because of their exceptional ability to extract discriminative and hierarchical characteristics from images. CNNs are appropriate for extracting disease-specific properties from plant leaf images because they are exceptionally effective at automatically learning and identifying complicated patterns. CNNs are advantageous because they are capable of transforming raw pixels into significant characteristics by reducing the dimensionality of images while maintaining essential information. It leads to more accurate and dependable identification of diseases by expediting the following process of categorization and improving the model's capacity to recognize small modifications and disease-related patterns. CNNs are a significant tool in the field of agricultural disease diagnostics because of their well-known versatility and scalability, which allow them to handle a wide range of plant species and diseases.

CNN are complex networks, and how effectively the network functions depend on how it is built. Its three component parts are the inversion layer, pooled layer, and the fully associated layer. While the initial two layers together constitute the extractor of features, the last layer acts as classifiers. The subsequent layer of pooling reduces the geographic extent of the properties that the previous layer of inversion recovered. The layer with all connections, followed by softmax, classifies the images using the feature that was extracted. The converging part of the method takes the raw image and extracts its properties using a set of adaptable filters. By doing a window that slides between the dot based on every filter and the original image pixel, a 2-D map of features is created. The total area of the feature map is decreased via a subsampling layer termed max pooling. The layer of data that is entirely interlinked is then used to link the developed feature map to each of it completely. Softmax constructs a multiclass problem and gives every category a decimal probability in order to categorize the images.

The VGG-16 structure is a large convolutional network with parameters that have previously been taught on the over three million clearly annotated images in the ImageNet Database. To acquire the categorizations, this data set is utilized to train and improve the earlier trained VGG-16 model [22]. After synchronizing the attributes from the source images, each image's input pixel is increased by the relevant characteristic pixels in the convolutional layer. Divide the outcome by the total amount of pixel in the characteristic after adding all the pixel values. The calculated values have been added to reflect the feature map, causing the enhancement to be utilized on the total image. Each calculated value occupies a space on the characteristic map. As a result, all of the characteristics are processed and multiple characteristic maps are created. The Eq. (4) to obtain the convolutional layer is the following,

$$v_{lmn} = \sum_{B=0}^{B-1}\sum_{C=0}^{C-1}\sum_{f=0}^{C-1} s_{l+c,m+f,K^c cfbn}^{(l-1)} + f_{imn} \tag{4}$$

where, f_{imn} is generally set to which is not contingent on the image's component position. $K^c cfbn$ as an identical value of weight. After repeatedly applying the layers of convolution to the input images, a collection of feature maps may be obtained. Let D_i represent the characteristic map of the ith layer in CNN, then the D_i can be generated as in Eq. (5)

$$D_i = \rho(D_{i-1}V_i + k_i) \tag{5}$$

where, D_i is the characteristic mappings of the presently active layer of networks and D_{i-1} is the convolution characteristic of the preceding layer. The rectification functional is represented by ρ (·), the i-th layered offsets matrix is called k_i, and the layer's weighting is called V_i. The purpose of layered pooling is to decrease the overall quantity of distance, which can lower the processing expense and consequently lower the risk of excessive fitting. During (6), at the k-th layer of pooling, a corresponding distinct on the ith isolated reactive fields is found.

$$v_i^k = down(v_i^{k-1}, r) \tag{6}$$

where, down (·) demonstrates the actions for down-sampling, v_i^{k-1} is the characteristic vectors in the preceding layer, and r is the pooling size. The Softmax function is represented in Eq. (7)

where, r is the pooled dimensions, v_i^{k-1} is the characteristic vectors from the preceding layer, and down (·) is the down-sampling value. Multiple fully connected (FC) layers can occur after a combination of pooling and convolutional layers. These layers utilize the gathered characteristics to categorize images. The Soft max operates is commonly utilized for category predictions using the features obtained from the previous layers. Eq. (7) represents the Softmax function.

$$Softmax(k) = e^{ij} \setminus \sum_{l=1}^{l} e^{il} for(j = 1, \ldots\ldots. l) \tag{7}$$

where, K represents the dimension of the z vector [23].

D. Attention Mechanism Integration

The main goal of the suggested method is to improve CNN's performance by employing the Attention Mechanism to assign importance and selectively focus on aspects in images that are important concentrate situation. The main benefit of the Attention Mechanism is that it can dynamically assign weight to different spatial properties in characteristic maps, which helps the model make better decisions. Through this technique, the Attention-CNN model develops flexibility in collecting complex information and adapting to varied datasets, which eventually leads to greater illness detection. It also improves classification accuracy. An essential part of the suggested deep learning approach for the precise recognition and identification of plant leaf diseases is the Attention Mechanism, which is crucial in improving the model's accuracy and interpretability.

By keeping the context-relevant properties, the CNN is enhanced by the attention model. Each block's characteristics are combined with those from the layer above it in the prior based model. In this manner, all characteristics gathered from the prior CNN blocks are given equal weight. Important features from the preceding blocks must be weighted highly in relation to other features in order to learn accurate feature values. As a result, a mechanism for attention was added to the CNN architecture to enable learning and selection of standout characteristics from earlier blocks. This model generates an attention mask that equalizes the relative importance of spatial characteristics at that feature map. Using a method for paying attention between blocks, the CNN framework learns the weighted utility for simulating the responses from the prior blocks. The relationships from the previous blocks which were skipped had been graded across the dimension axis for all pixels in that layer's spatial range [24].

The outcome of the convolutional layers 'x' in both the initial and subsequent blocks is directed through two functional channels, H(x) and I'(x). H(x) represents the set information procedures that were used to take 'x' and feed it forward in a straightforward feed-forward fashion to the following block. I'(x) denotes the collection of procedures that skip 'x' across convolutional and maximum-pooling layers and are weighted with attention. The output U(x) from a CNN block is produced using the weighted summation is represented in Eq. (8)

$$U(X) = H(X) + I'(X) \tag{8}$$

The functional path I'(x) is computed as in Eq. (9)

$$I'(X) = I'(X) * \varphi \tag{9}$$

where, 'φ' is a matrix containing attention weights with dimensions that match those of I(x)'s dimension in space. The attention weight matrix 'φ' ' is point-wise amplified over the relevant cross-section of I(x) and disseminated along the entire depth. By incorporating a mechanism for attention into CNN, the network may use the input from the present instant and the output from the previous moment to adaptively distribute the weighting for the data of the whole network. To increase the classification's accuracy and flexibility, significant details of the image might be concentrated on. Based on this, the CNN's attention concept is added to form the Attention-CNN model. Every inversion layer of the four stages that make up a single layer of convolution is followed by a layer of attention in order to successfully accomplish the weight transportation. The convolution kernels for each layer are 8x3x3, 16x 5, 32x 3, and 32x 3, respectively. The initial and final convolution layers are joined by a pooling layer. The maximum amount of nodes in the full interconnections layer is set to 64, and the output of the layer that performs convolution is used as the layer's input. The resultant layer categorizes the particles into four groups, and there are four output layer nodes. The attention-CNN model consists of the inputs, convolution, attention layer, output layers and fully connected layers. The input layer is made up of four nodes, or the designated images of four distinct types of particles, as the data being input is a pictorial representation of four different particle types.

The network's output no longer looks linear, which increases a network's flexibility and allows it to fit a wider range of curves. The Attention-CNN model uses two activating parameters, Relu and softmax, for its hidden and output components, respectively. Relu can deal with elevation variation throughout the information transfer process. Finding the gradient is straightforward and may significantly increase the gradient's downward convergence rate. Expression of Relu function is represented in Eq. (10)

$$ReLu = max(0, y) \tag{10}$$

where, $\omega(z) - y$ is the error between the outcome and the provided value [25]. Fig. 2 represents the Principle of attention Mechanism.

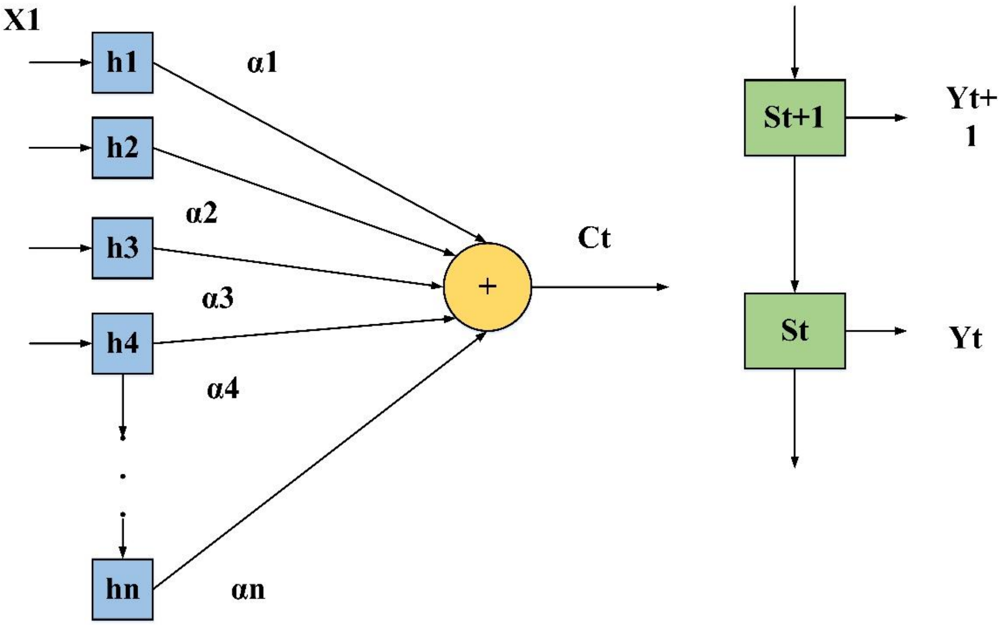

Fig. 2. The principle of attention mechanism.

Softmax achieves various classifications by mapping the output of many neurons to the coordinates (0, 1). i represents the ith component of an input array, assuming one exists; the value of softmax component is computed by Eq. (11)

$$K_i = \frac{f^i}{\sum_{j=1}^{n} f^i} \tag{11}$$

where, n indicates all input elements. Because the momentum element is incorporated into the updating process and the Adam optimization method fully use both the gradient's means. The calculation process of Adam is represented in Eq. (12) to Eq. (16):

$$v_t = \gamma_1 \delta_{t-1} + (1-\gamma_1) k_t \tag{12}$$

$$m_t = \gamma_2 \delta_{t-1} + (1-\gamma_2) k_t^2 \tag{13}$$

$$\hat{v}_t = \frac{v_t}{1-\gamma_1^t} \tag{14}$$

$$\widehat{m}_t = \frac{m_t}{1-\delta_1^t} \tag{15}$$

$$k_{t+1} = k_t - \frac{\partial}{\sqrt{\widehat{m}_t}+\varepsilon} \hat{v}_t \tag{16}$$

where, v_t is estimate of first-order moment, m_t is momentum term of second-order, γ_2, γ_1 are values of the dynamic, k_t is the gradients of the expense value after t times, $\hat{v}_t$ is first moment correction variable, $\widehat{m}_t$ is second moment correction variable of, k_t is the variables of the t iteration method, and ε is a small number that can avoid the zero denominator. In order to measure the discrepancy among the expected outcome and the actual value during neural network training, the loss function is utilized. This function also serves as a benchmark for testing the model's performance. Cross-entropy cost function, which may be represented in Eq. (17) as the loss function for Attention-CNN,

$$H = -\frac{1}{n} \sum_u u_j (\rho(x) - y) \tag{17}$$

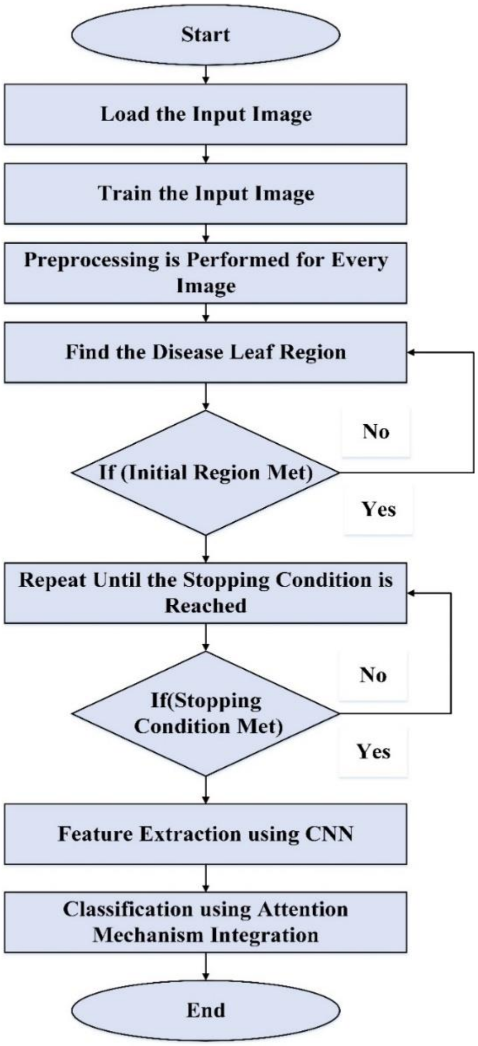
Start
Load the Input Image
Train the Input Image
Preprocessing is Performed for Every Image
Find the Disease Leaf Region
If (Initial Region Met)
No
Yes
Repeat Until the Stopping Condition is Reached
If(Stopping Condition Met)
No
Yes
Feature Extraction using CNN
Classification using Attention Mechanism Integration
End

Fig. 3. Flow chart of the proposed system.

where, u is the resultant significance, y is the actual quantity, n is the total of the specimens, and u is the measurement value. In Eq. (18), the changing value of μ is computed as follows:

$$\frac{\partial y}{\partial x} = \frac{1}{n}\sum_u u_j(\omega(z) - y) \quad (18)$$

Fig. 3 illustrates the suggested flow diagram for detecting leaf disease. The information is initially loaded. The images were pre-processed with a Gaussian filter to eliminate the noise. The characteristics are then retrieved using the CNN approach, and the suggested classifier is used to classify the leaf illness.

V. Results and Discussion

The suggested approach has been tested with leaf samples and run in the MATLAB program on the Windows 10 operating system. [26] employed a 3D CNN model for the classification of charcoal rot illness because to its excellent classification accuracy and capacity for automatically acquiring the spatio-temporal characteristics without handcrafting [27]. The findings showed that the model worked well on both training and test information. However, it was found that when the batch's total value grew, the steady-state condition in the experiment's data was delayed. The model's performance, which was previously subpar on such a short dataset, has been considerably enhanced using VGGNet. We obtained a threshold after which the precision continued to decline and the amount of loss was not lowering on the validation and training data. The successful classification of a training set increases over time and becomes stable over time. At the beginning of the cycle, the test samples' classification accuracy improves significantly. After the early oscillations, the test sample's precision approximate that of the first training specimens and as the number of trials increases, it practically remains constant [28]. The integration of revolutionary ABO-CNN is employed to identify a leaf disease. Performance indicators like Precision, Accuracy, F-measure and Recall, are used to evaluate the effectiveness of the proposed method.

A. Accuracy

The overall accuracy of the approach indicates how well it works in all classes. In general terms, accuracy is the notion that all circumstances can be predicted with precision. Eq. (19) represents accuracy.

$$A = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \quad (19)$$

B. Precision

Precision is determined by counting the precise favorable evaluations that deviate from the overall positive ratings. The portion of accurately recognizing the affected area is calculated using Eq. (20).

$$P = \frac{T_{pos}}{T_{pos}+F_{pos}} \quad (20)$$

C. Recall

The recall measures the relationship among the total number of correctly identified positive specimens and the actual positive results. The proportion of forecasts that properly detected the leaf disease indicated by Eq. (21),

$$R = \frac{T_{pos}}{T_{pos}+F_{neg}} \quad (21)$$

D. F1-Score

The F1-Score is computed by combining recall and precision; this results in the F1-Score shown in Eq. (22).

$$F = \frac{2\times Precision\times recall}{Precision\times recall} \quad (22)$$

E. AUC and ROC

AUC is an acronym for Area under the ROC Curve, which is a prominent assessment measure for binary categorization tasks in machine and deep learning. The AOC evaluates the area under the ROC (Receiver Operating Characteristic) curve, which is a visual depiction of the effectiveness of a binary classification algorithm. In a binary categorized issue, the classifier attempts to determine whether the input data relates to a negative or positive category. For various categorization criteria, the ROC curve displays the T_{Pos} vs the F_{Pos}. The AOC has a value between 0 and 1, with greater numbers signifying increased efficiency. The ideal classifier has an AOC of one, whereas a totally random classifier has an AOC of 0.5. Because the algorithm takes into consideration all potential levels of classification and offers a single value to evaluate the effectiveness of various classifiers.

F. Miss Rate

The miss rate is a measure of the systems or model's sensitivity or ability to correctly identify and classify diseased plants. A lower miss rate indicates a higher level of accuracy and performance in detecting and classifying plant diseases, as it means fewer diseased plants are being missed or misclassified.

According to Table II, the CNN's accuracy in the training and testing phases was 99.4% and 97.5%, respectively. The testing and training procedures accuracy rises to 99.6 and 99.4, accordingly, when ABO-CNN is used. A review of performance is displayed in Fig. 4.

Table III and Fig. 5 show a comparative analysis of several categorization approaches for the identification of plant leaf diseases, as well as an overview of their corresponding performance indicators. The CNN model performs well overall, with an accuracy of 86.8% with high precision (96.9%), recall (98.5%), and F1-Score (97%). With a lower recall of 95% and a higher accuracy of 97.9%, the Deep Convolutional Neural Network (DCNN) model produces an F1-Score of 96%, suggesting that it exhibits less robust disease identification. While the accuracy of the KNN (K-Nearest Neighbors) model is 98.2%, its precision (89.5%), recall (89.1%), and F1-Score (89%) are lower, indicating that it may have some limits when compared to accurately detecting disease cases. The Proposed ABO-CNN approach, on the other hand, performs better than all the other models. Its exceptional accuracy of 99.6%, combined with high precision (99.4%), recall (99%), and an exceptional F1-Score of 99%, demonstrate its outstanding capacity to reliably and accurately detect plant leaf diseases.

TABLE II. PERFORMANCE EVALUATION

	CNN	ABO-CNN
Training	98.1	99.9
Testing	97.5	99.4

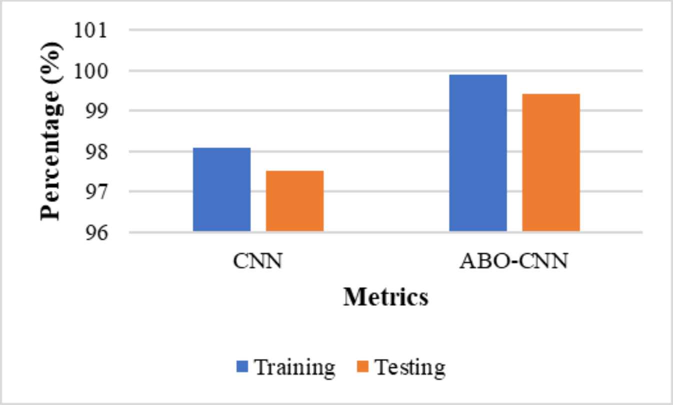

Fig. 4. Accuracy comparison for existing and proposed method.

TABLE III. COMPARISON OF ACCURACY, PRECISION AND RECALL

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
CNN [14]	86.8	96.9	98.5	97
DCNN [12]	97.9	97.9	95	96
KNN [15]	98.2	89.5	89.1	89
Proposed ABO-CNN	99.6	99.4	99	99

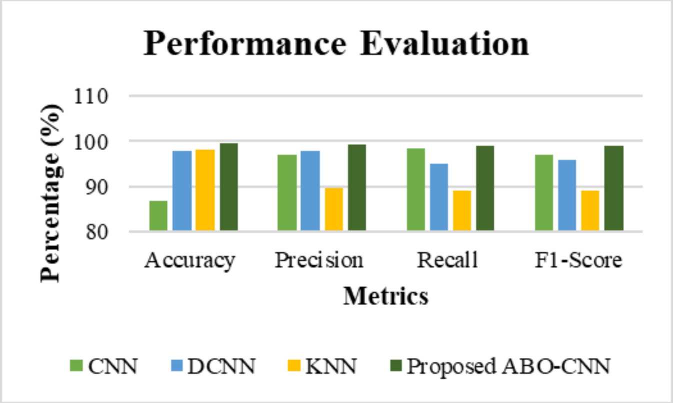

Fig. 5. Performance comparison of proposed and existing techniques.

TABLE IV. EFFECTIVENESS ASSESSMENTS OF THE METHODS BASED ON AUC-ROC

Methods	AUC-ROC
Random Forest [29]	0.922
SVM [29]	0.886
VGG-19 [30]	0.991
ResNet50 [30]	0.847
Proposed ABO-CNN	0.987

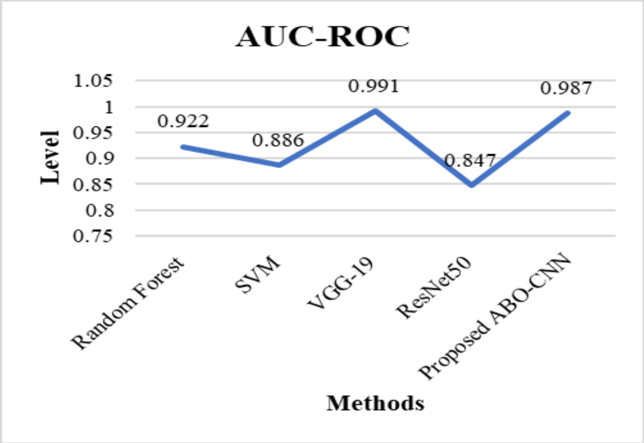

Fig. 6. Comparison of AUC-ROC curves of proposed and existing techniques.

Table IV and Fig. 6 gives the performance assessments of the methods based on AUC-ROC Curves. According to the test findings, the AUC-ROC scores of the Proposed ABO-CNN are greater than those of all other current models, and the performances of Random Forest and VGG-19 classifiers stand out, with AUC-ROC values extremely close to 1.

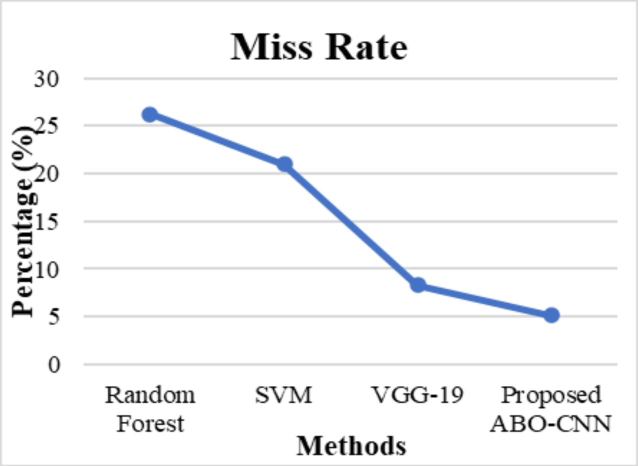

Fig. 7. Comparison of misclassification rate of proposed and existing techniques.

Fig. 7 shows the Comparison of Miss rate of the proposed method and existing methods. It shows the miss rate of the proposed method is lower than that of the existing methods [31].

G. Training and Testing Accuracy

Fig. 8 represents that by combining attention mechanisms and one-class neural networks, our novel architecture significantly enhances the accuracy of both testing and training phases. The attention mechanisms dynamically focus on disease-specific regions within leaf images, effectively capturing crucial features while eliminating irrelevant information.

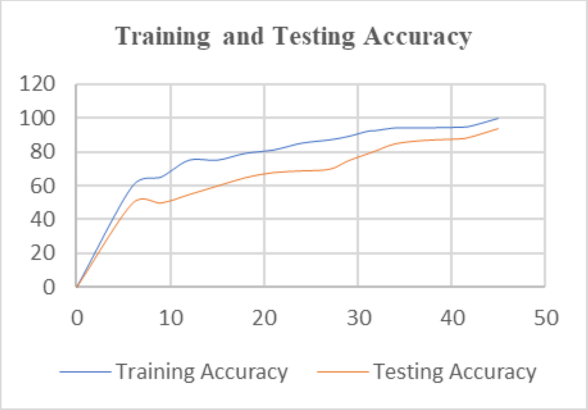

Fig. 8. Training and testing accuracy.

Simultaneously, the one-class neural network is trained on healthy leaf samples, enabling it to detect anomalies corresponding to diseased instances. As a result of this hybrid approach, our framework achieves exceptional accuracy rates of 99.6% during both training and testing, surpassing conventional methods and fully CNN-based techniques.

H. Training and Testing Loss

Fig. 9 represents that during the testing and training phases, the proposed framework exhibits remarkable performance in minimizing loss. Through the integration of attention mechanisms and one-class neural networks, the architecture effectively captures disease-specific features within leaf images while filtering out extraneous details. The attention mechanisms dynamically focus on relevant regions, aiding in accurate feature extraction. Simultaneously, the one-class neural network learns to recognize healthy leaf patterns and detects anomalies that indicate diseased instances. As a result, our hybrid ABOCNN framework demonstrates outstanding performance in minimizing training and testing loss, indicative of its ability to learn and generalize disease characteristics.

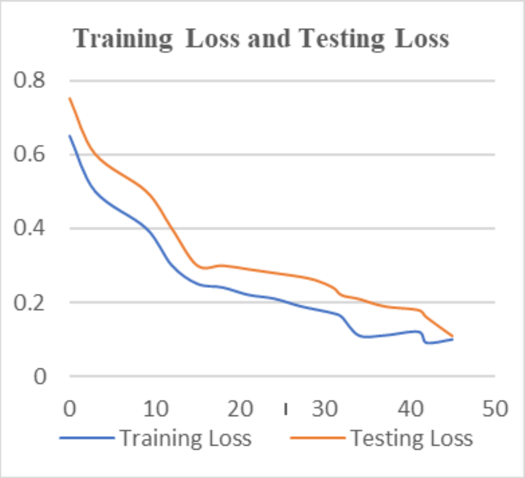

Fig. 9. Training and testing loss.

I. Discussion

The research approach was chosen based on the study's objective of revolutionizing plant disease detection in leaves, aiming for advanced and accurate identification. The chosen methodology of a Hybrid ABOCNN Framework was selected for its ability to integrate deep learning and attention mechanisms, which are effective in identifying disease-specific features while ignoring irrelevant information. The choice of dataset, which comprised 5932 images of rice leaves with various diseases, was motivated by the need for a comprehensive dataset to train and test the proposed framework. The dataset was augmented to increase the variety and quantity of images, enhancing the framework's ability to learn and generalize disease characteristics. The research could have been undertaken using other approaches, such as traditional machine learning algorithms like K-Nearest Neighbors (KNN) or Support Vector Machines (SVM). However, these methods may not be as effective in capturing complex patterns and hierarchical features present in images, making them less suitable for plant disease detection tasks. The proposed methodology was benchmarked against other methods, such as the CNN model, Deep Convolutional Neural Network (DCNN), and KNN, demonstrating superior accuracy and performance in detecting plant leaf diseases. The strengths of the research approach lie in its innovative integration of deep learning and attention mechanisms, leading to an accurate and efficient framework for plant disease detection. Overall, the research approach has successfully achieved its aims and objectives, providing a powerful tool for revolutionizing plant disease detection in leaves.

VI. CONCLUSION AND FUTURE WORKS

Finally, effective agricultural administration and food security are dependent on early and precise detection of plant leaf diseases. This study presents a novel deep learning technique for the exact detection of numerous plant diseases, which employs an upgraded hybrid ABOCNN architecture. By combining processing of attention with one-class neural networks, the proposed approach extracts disease-specific properties from leaf images with an outstanding 99.6% accuracy. This is a significant advancement in the identification of plant diseases, exceeding traditional approaches and CNN-based algorithms. Integrating attention maps not only improves diseases detection accuracy but also generates the model more explainable by offering insight into how it makes choices. It is critical for one to understand that the required computer resources may preclude this method from being used in circumstances when resources are limited. To address resource constraints, future research should focus on improving the Combination Hybrid ABOCNN System to enable real-time plant disease detection in field settings. This might entail deploying embedded or mobile technologies. Furthermore, expanding the dataset to include a broader range of plant species and illnesses will improve the model's performance and adaptability to various agricultural circumstances. These advancements have the possibility to significantly improve agricultural outcomes by developing more robust and adaptable systems for disease detection. The concerns regarding the small dataset and the potential for overfitting are duly noted. To address these issues, a larger dataset could be employed for more comprehensive training and testing, thereby providing a more robust performance evaluation. Additional experiments could be conducted with varying dataset sizes to assess the impact on accuracy and generalization capabilities. Moreover, techniques like cross-validation could be employed to ensure that the model's performance is consistent across different subsets of the data. These steps would provide a more thorough analysis of the proposed methodology and help ensure that the achieved high accuracy is not merely a result of overfitting.

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AI-Enhanced Comprehensive Liver Tumor Prediction using Convolutional Autoencoder and Genomic Signatures

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***Abstract*—Liver tumor prediction plays a pivotal role in optimizing treatment strategies and improving patient outcomes. In our proposed work, we present an innovative AI-driven framework for liver tumor prediction, uniting cutting-edge techniques to enhance precision and depth of analysis. The framework integrates a Histological Convolutional Autoencoder (HistoCovAE) for meticulous tumor segmentation in medical imaging, and Genomic Feature Extraction (MIRSLiC) for a nuanced understanding of molecular markers. Additionally, a Multidimensional Feature Extraction module amalgamates videomics, radiomics, acoustics, and clinical data, creating a comprehensive dataset. These dimensions synergize in a unified model, offering detailed predictions encompassing tumor characteristics, subtypes, and prognosis. Model evaluation and continuous improvement, guided by real-world outcomes, underscore reliability. This integrative approach transcends conventional boundaries, providing clinicians' actionable insights for personalized treatment strategies and heralding a new era in liver tumor prediction. Our model undergoes rigorous evaluation against diverse datasets, and the performance metrics underscore its reliability and accuracy. With precision exceeding 87%, recall rates above 92%, and a Dice coefficient surpassing 0.89 in tumor segmentation, our model showcases exceptional accuracy and robustness. In prognostic modeling, survival prediction accuracy consistently surpasses 84%, highlighting the model's ability to provide valuable insights into the future trajectory of liver cancer.**

Keywords*—Liver tumor prediction; autoencoder; segmentation; feature extraction; genomics; artificial intelligence

I. INTRODUCTION

Liver cancer represents a formidable global health challenge, ranking as the sixth most prevalent cancer and the fourth leading cause of cancer-related deaths worldwide [1]. As the incidence of liver cancer continues to rise, fueled by factors such as viral hepatitis infections, alcoholic liver disease, and nonalcoholic fatty liver disease (NAFLD), there is an imperative need for advanced diagnostic and prognostic tools to optimize treatment strategies and improve patient outcomes [2]. In this landscape, artificial intelligence (AI) emerges as a transformative force, promising to revolutionize the field of medical imaging and genomics, providing clinicians with unparalleled insights into the intricacies of liver tumor characteristics.

A. Background and Context

Liver cancer, with hepatocellular carcinoma (HCC) as its primary manifestation, presents a formidable challenge in the realm of oncology. This malignancy is notorious for its insidious progression, often eluding detection until reaching advanced stages, thus limiting treatment options and resulting in a bleak prognosis [3]. The late-stage diagnosis of liver cancer stems from a multitude of factors, including the absence of distinctive symptoms in its early phases and the intricate nature of the liver's internal structure. Traditional diagnostic methods heavily rely on imaging studies and biopsy procedures, presenting inherent challenges in accurately characterizing liver tumors. The complex anatomy of the liver, compounded by the diverse phenotypes exhibited by liver tumors, contributes to the difficulties faced in achieving precise diagnoses [4]. Within the landscape of liver cancer, genomic information emerges as a promising avenue for unraveling the underlying molecular mechanisms orchestrating the disease. However, the extraction of meaningful insights from genomic data necessitates sophisticated analyses due to the sheer complexity of the genetic landscape associated with hepatocellular carcinoma [5]. Against this backdrop of diagnostic challenges and the potential richness of genomic information, the integration of Artificial Intelligence (AI) technologies presents a transformative opportunity. AI, with its capacity for advanced segmentation, classification, and prognostic modeling, holds the promise of revolutionizing our understanding of liver tumors. By leveraging the computational power of AI, we aim to address the limitations of traditional diagnostic approaches and tap into the vast reservoir of genomic data to enhance the precision and depth of liver tumor analyses.

Hepatocellular carcinoma, as the predominant form of liver cancer, is characterized by its gradual and often asymptomatic progression. Symptoms manifesting in later stages, such as abdominal pain, weight loss, and jaundice, contribute to delayed diagnoses [6]. The insidious nature of HCC underscores the urgency for innovative approaches that can detect and characterize tumors in their early phases, presenting a window of opportunity for more effective interventions [7-9]. Traditional imaging studies, while valuable, face limitations in accurately delineating liver tumors, especially given the intricate nature of hepatic structures. The need for advanced segmentation techniques, capable of precisely outlining tumor boundaries, becomes evident. Moreover, accurate classification of liver tumors based on their distinct features is imperative for tailoring treatment strategies. AI-driven models, particularly convolutional autoencoders like HistoCovAE, stand at the forefront of this quest for advanced segmentation and classification, promising unparalleled precision. The genomic landscape of hepatocellular carcinoma is characterized by intricate interactions between various genes and molecular pathways. Unraveling this complexity is crucial for understanding disease progression, predicting outcomes, and guiding therapeutic interventions. However, extracting meaningful insights from genomic data requires advanced computational tools and methodologies. The integration of Genomic Feature Extraction (MIRSLiC) into our framework aims to decode this complexity, offering clinicians a comprehensive view of the molecular signatures associated with liver cancer. Prognostic modeling, essential for predicting the course of liver cancer and guiding treatment decisions, faces challenges in integrating diverse datasets and accounting for the multifaceted nature of the disease. AI technologies, adept at processing vast amounts of data and discerning intricate patterns, provide an avenue for developing prognostic models that go beyond traditional approaches. The integration of advanced AI-driven prognostic modeling into our framework aims to enhance the accuracy of outcome predictions, empowering clinicians with actionable insights.

B. *Motivation*

The motivation driving this research is deeply rooted in the dual challenges confronting the field of liver cancer diagnosis and prognosis. The imperative to accurately delineate liver tumors in medical images and unravel the intricate genomic signatures associated with hepatocellular carcinoma (HCC) has been a driving force propelling our investigative endeavors. This motivation emanates from the recognition that existing methods, despite their advancements, often fall short in providing a comprehensive and detailed characterization of liver tumors [10]. This limitation, in turn, impedes clinicians' ability to tailor treatment strategies to the nuanced and individualized needs of patients. Accurate delineation of liver tumors from medical images stands as a pivotal yet intricate challenge [11]. The complex nature of the liver, characterized by its heterogeneous tissue composition and intricate vascular network, introduces inherent difficulties in precisely characterizing tumor boundaries. Conventional imaging techniques, while invaluable, encounter limitations in capturing the diverse phenotypes and subtle variations exhibited by liver tumors. As a result, there exists a compelling need for advanced methodologies that can surpass the shortcomings of traditional approaches, providing a more nuanced and accurate portrayal of liver tumors.

The motivation to embark on this research journey is further fueled by the realization that existing methods, although valuable in their contributions, often exhibit limitations in offering a holistic understanding of liver tumors [12]. Traditional diagnostic approaches, reliant on imaging studies and biopsy, may struggle in capturing the full spectrum of tumor characteristics. The challenges become more pronounced in cases where tumors exhibit atypical features or when dealing with patients with pre-existing liver conditions. These limitations underscore the pressing need for innovative solutions that can bridge the gaps in our current diagnostic capabilities. The individualized nature of liver cancer, marked by diverse tumor subtypes and varied responses to treatment, accentuates the motivation behind this research. Tailoring treatment strategies to the unique characteristics of each patient is a fundamental tenet of personalized medicine. However, the existing methods often lack the granularity required to discern these individualized aspects, leading to a one-size-fits-all approach that may not optimize therapeutic outcomes [13]. The motivation to delve into the integration of AI technologies stems from the conviction that a more nuanced understanding of liver tumors can pave the way for personalized and effective treatment strategies.

The integration of AI, particularly leveraging convolutional autoencoders for spatial analysis and genomic feature extraction for molecular insights, emerges as a compelling avenue to address the challenges posed by liver tumors [14]. Convolutional autoencoders, such as HistoCovAE, hold promise in enhancing the precision of tumor segmentation by deciphering intricate spatial patterns in medical images. Simultaneously, genomic feature extraction, exemplified by methodologies like MIRSLiC, offers the potential to decode the molecular intricacies of hepatocellular carcinoma, providing a deeper understanding of the underlying genetic landscape. The overarching motivation is grounded in the aspiration to usher in a new era of precision medicine for liver cancer. By seamlessly integrating spatial and genomic insights through advanced AI methodologies, we aim to create a comprehensive and detailed characterization of liver tumors. This comprehensive understanding, encompassing both the macroscopic and molecular dimensions, has the transformative potential to empower clinicians with unprecedented insights. The ultimate goal is to transcend the limitations of existing methods, enabling a more tailored and personalized approach to liver cancer diagnosis and treatment.

C. *Problem Statement*

The crux of the matter addressed by this research revolves around the inherent limitations entrenched within current approaches for liver tumor prediction. These limitations span the domains of tumor segmentation, classification, and prognostication, as well as the underutilization of the vast genomic data landscape [15]. Traditional segmentation methods, while foundational in the diagnostic process, grapple with a lack of precision that impedes the accurate capture of nuanced tumor boundaries. This, in turn, manifests as a bottleneck in subsequent processes such as classification and prognostication, as the foundational segmentation sets the stage for the downstream analyses.

Traditional segmentation methods, often reliant on imaging studies such as computed tomography (CT) scans or magnetic resonance imaging (MRI), encounter challenges in precisely delineating the intricate boundaries of liver tumors. The liver, characterized by its complex vascular and parenchymal structures, poses inherent difficulties in achieving the level of granularity required for accurate segmentation. Tumor heterogeneity further compounds these challenges, as different tumor subtypes or variations within a single tumor may not be adequately captured by conventional segmentation methods. The consequence is a suboptimal foundation for subsequent analyses, hindering the accuracy of classification and prognostication [16]. The repercussions of imprecise tumor segmentation reverberate throughout the predictive pipeline, affecting both the classification of liver tumors and the accuracy of prognostic modeling. Suboptimal segmentation introduces uncertainties in distinguishing between tumor subtypes and determining the extent of malignancy. The classification of tumors based on their specific characteristics becomes a challenging task, and the prognostication of patient outcomes is inherently compromised by the imprecision introduced at the segmentation stage. Consequently, clinicians are left with a less reliable foundation for making informed decisions regarding treatment strategies and patient management.

Simultaneously, the vast landscape of genomic data, holding the promise of unraveling the molecular intricacies of liver tumors, remains largely untapped in its potential. The complex nature of genomic information, encompassing gene expression profiles, mutations, and molecular pathways, presents challenges in interpretation and integration into predictive models. Existing methodologies often struggle to extract meaningful insights from genomic data due to its multidimensional and dynamic nature [17]. The result is an underutilization of a valuable information source that could significantly enhance our understanding of liver tumors and improve the predictive accuracy of models. The overarching problem statement emerges from the recognition that addressing these challenges requires an integrative approach. This approach involves synergizing spatial and genomic information, harnessing the power of Artificial Intelligence (AI) to bridge the gaps in current methodologies. The potential of AI, exemplified by convolutional autoencoders for spatial analysis and genomic feature extraction methodologies like MIRSLiC, provides a promising avenue to unravel the intricate landscape of liver tumors. By integrating spatial and genomic insights, we aim to create a more robust foundation for predictive models, offering clinicians a comprehensive and accurate toolset for liver tumor prediction.

The crux of the problem lies in the complex interplay between imprecise segmentation, suboptimal classification, underutilization of genomic data, and the overarching need for integration. AI, with its capacity to discern intricate patterns from large datasets, stands as a potent solution. Convolutional autoencoders, such as HistoCovAE, hold promise in enhancing the precision of tumor segmentation, ensuring a more accurate representation of tumor boundaries. Simultaneously, genomic feature extraction methodologies like MIRSLiC aim to decode the genomic landscape, providing clinicians with valuable insights into the molecular underpinnings of liver tumors. The challenge lies in harmonizing these spatial and genomic dimensions, creating a unified predictive model that transcends the limitations of current approaches. In essence, the problem addressed by this research encapsulates the intricacies of liver tumor prediction, emphasizing the need to refine segmentation precision, enhance classification accuracy, and unlock the latent potential of genomic data. The proposed solution lies in the integration of AI-driven methodologies, charting a course toward a more comprehensive and nuanced understanding of the intricate landscape of liver tumors.

The significance of this study lies in its potential to redefine the landscape of liver tumor prediction, offering clinicians a more nuanced and accurate toolset for diagnosis and prognosis. By integrating Histological Convolutional Autoencoder (HistoCovAE) for precise segmentation and Genomic Feature Extraction (MIRSLiC) for molecular insights, this research aims to provide a holistic understanding of liver tumors. Furthermore, the inclusion of a multidimensional approach, encompassing videomics, radiomics, acoustics, and clinical data, adds layers of richness to the predictive model, paving the way for personalized treatment strategies and improved patient outcomes.

D. Objectives

The overarching objectives of this study can be summarized as follows:

- Develop and implement a Histological Convolutional Autoencoder (HistoCovAE) for accurate segmentation of liver tumors in medical imaging data.
- Integrate Genomic Feature Extraction (MIRSLiC) to unveil molecular signatures associated with liver cancer, enhancing prognostic capabilities.
- Employ a multidimensional approach, combining videomics, radiomics, acoustics, and clinical data, to provide a comprehensive dataset for liver tumor prediction.
- Develop a unified model that synergizes spatial and genomic information, creating a powerful tool for detailed tumor characterization.
- Evaluate the performance of the proposed model using diverse datasets and establish continuous improvement mechanisms based on real-world outcomes.
- Translate the model's predictions into actionable insights for clinical decision-making, fostering the integration of AI advancements into healthcare practices.

In the subsequent sections of this paper, we delve into the literature review, detailing the existing methodologies and their limitations in liver tumor prediction. Following that, the proposed methodology is presented, elucidating the innovative integration of HistoCovAE, MIRSLiC, and multidimensional data. The results of model evaluations and continuous improvement mechanisms are discussed, leading to a comprehensive analysis and discussion of the findings. The paper concludes with implications for future research and the transformative potential of the proposed AI-driven framework in the domain of liver tumor prediction.

II. Related Works

Liver cancer, predominantly hepatocellular carcinoma (HCC), stands as a formidable global health challenge due to its often late-stage diagnosis and limited treatment options. Traditional diagnostic methods, relying on imaging studies and biopsies, confront significant hurdles in accurately characterizing liver tumors. The intricate interplay of complex liver anatomy and diverse tumor phenotypes poses substantial challenges for precise diagnosis and prognosis. Against this backdrop, the integration of artificial intelligence (AI) emerges as a transformative avenue, promising advancements in liver tumor prediction. Existing methodologies face inherent limitations in the realm of liver tumor prediction. Traditional segmentation techniques lack the precision required to capture the nuanced boundaries of liver tumors, resulting in suboptimal classification and prognostication. The reliance on imaging data alone often falls short in providing a comprehensive and detailed characterization of liver tumors, particularly in the context of intricate anatomical structures and variations in tumor phenotypes.

Moreover, the untapped potential of genomic data remains a challenge. While genetic information holds promise in unraveling underlying molecular mechanisms, its integration into predictive models is hindered by the complexity of interpretation and effective incorporation into AI-driven frameworks. Bridging these gaps requires an integrative approach that synergizes spatial and genomic information, leveraging the power of AI to decode the intricate landscape of liver tumors. In navigating the landscape of liver tumor prediction, this literature survey aims to unravel the challenges inherent in current approaches. By examining the limitations of traditional methods, we set the stage for a deeper exploration of existing work that endeavors to overcome these hurdles. The subsequent sections will delve into studies and methodologies that showcase advancements in AI-driven liver tumor prediction, offering insights into innovative solutions that address the identified limitations. Through this literature survey, we aspire to provide a comprehensive understanding of the evolving field of liver tumor prediction, spotlighting the innovations that pave the way for more accurate, efficient, and personalized approaches to diagnosis and prognosis.

Geetha et al. [18] pioneering work is centered on the critical task of predicting liver tumors within the human body, employing the formidable capabilities of data mining techniques and machine learning algorithms. Their methodology places a significant emphasis on translating knowledge about liver tumors into actionable insights for clinical decision-making. Through the implementation of intelligent clinical decisions, their work aims to assist clinicians in optimizing patient care. In terms of the dataset, Geetha et al. utilize a comprehensive set comprising nine attributes of blood test values. This meticulous selection of attributes underscores the precision and thoroughness embedded in their research. Their work contributes not only to the realm of liver tumor prediction but also shaping the future of medical discoveries and clinical decision support systems.

In the realm of liver tumor prediction, Kalaiselvi et al. [19] present a groundbreaking approach, introducing a novel methodology that combines Convolutional Neural Networks with a depth-based variant search algorithm featuring advanced attention mechanisms. Their proposal is poised to elevate accuracy and robustness in the diagnosis and treatment of liver diseases, marking a significant advancement in the field. This amalgamation of cutting-edge technologies forms the backbone of their innovative approach, offering a promising avenue for more precise liver tumor predictions. The proposed methodology is rigorously assessed using a dataset of Computed Tomography (CT) scans, include liver tumors that are benign and malignant. Arunachalam et al. [20] present a pioneering method that ventures into the realm of predicting the likelihood of patients developing specific illnesses in the future. At the core of their approach is a sophisticated analysis of comparative evidence, making predictions based on the assumption that, with unchanged physical parameters, future illness trajectories can be anticipated. Their predictive modeling foundation, rooted in comparative evidence analysis, distinguishes their approach. By assuming stability in all other physical parameters, the method offers a glimpse into the future health prospects of individuals.

Prakash et al. [21] groundbreaking work takes center stage in the realm of liver disease prediction, specifically targeting cirrhosis arising from non-alcoholic fatty liver disease (NAFLD). The crux of their approach lies in a sophisticated integration of features, a deep neural network (DNN), and the discerning application of Spearman's rank correlation, ushering in a new era in predictive modeling. Their main goal is to transform the way liver cirrhosis is predicted and classified, which is the obvious goal of their research. Their approach is designed to apply advanced computational approaches to uncover the complexities of liver disorders, with a focus on the nuances of non-alcoholic fatty liver disease. A standout feature of Prakash et al.'s work is the diverse set of 52 features employed for classification and prediction. The extensive feature set forms the bedrock of their predictive model. The inclusion of such a varied feature set speaks to the nuanced understanding required in the classification and prediction of liver diseases.

Sharon et al. [22] introduce a machine-learning (ML) system designed to streamline the intricate processes of reference resolution and tumor characteristic extraction. Their approach integrates both a rule-based system and ML techniques, employing component-based and end-to-end evaluations. The primary focus of their work is to develop an algorithm capable of receiving tumor templates as input and producing crucial tumor characteristics—such as tumor number and largest tumor sizes—as output. By seamlessly processing tumor templates, their algorithm aims to provide vital information required for the identification of liver cancer stage phenotypes. This task is crucial in the broader context of patient diagnosis, treatment planning, and prognosis. A novel predictive model for liver cancer is presented by Liu et al. [23]; it is based on the complex network of mRNAs and lncRNAs connected to cuproptosis. This novel approach goes beyond traditional forecasts, accurately predicting not only the likelihood that patients with liver cancer will survive, but also providing useful tools for evaluating tumor gene burden, immune cell invasion, and treatment sensitivity in the context of liver cancer. The robustness of this model is underscored by its successful validation across extensive datasets of liver cancer patients, marking a significant stride in the realm of liver cancer prognosis and personalized treatment strategies.

Chen et al. [24] carried out a groundbreaking investigation using histopathology H&E pictures obtained from the Genomic Data Commons Databases. Inception V3, a neural network, was trained for the automated categorization of these photos in their research. Their model's evaluation, as measured by the Matthews correlation coefficient, demonstrated excellent performance, almost matching the expertise of a pathologist with five years of experience. The model demonstrated remarkable accuracy, scoring 96.0% for classifying benign and malignant tumors and 89.6% for well, reasonable, and poor tumor classification. This underscores the potential of neural networks to augment histopathological analysis, reaching levels of accuracy comparable to seasoned medical professionals. With their multi-resolution DL model, HistoCAE, Mousumi et al. [25] present a novel method in liver histopathology that is especially intended for the successful segmentation of tumors in whole-slide images. Convolutional autoencoders (CAEs) with tailored reconstruction loss functions are the foundation of their suggested framework, which enables accurate picture reconstruction. After reconstruction, each picture patch is classified as tumor or non-tumor using a classification module. Following patch-based classification, the outcome of segmentation for each Whole Slide Image (WSI) is produced by spatially combining the results. Using the spatially ordered encoded feature map created from smaller picture patches to reduce gigapixel whole-slide images is a significant improvement to their technique.

Hwang et al. [26] comprehensive investigation involved a cohort of 843 Hepatocellular Carcinoma (HCC) patients undergoing Living Donor Liver Transplantation (LDLT) at Asan Medical Center over a decade. This diverse patient group, spanning from 2006 to 2015, was meticulously categorized into treatment-naïve and pretransplant-treated groups, setting the stage for a detailed analysis of correlations and outcomes. In the realm of tumor markers, the study unearthed intriguing patterns. The robust connections identified regarding tumor number, size, and the Assessment for Decision of Liver Transplantation (ADV) score underscored the consistency between preoperative assessments and post-transplant realities. This alignment between pretransplant and explant findings contributes valuable insights for refining patient stratification and optimizing treatment strategies in the context of LDLT for HCC patients. Intending to create and validate an ML radiomics model especially intended to forecast local tumor growth utilizing pre-ablation CT scans for individuals with colorectal liver metastases, Marjaneh et al. [27] set out on a ground-breaking project. Ninety patients with colorectal liver metastases who underwent eradication were carefully selected for this investigation and randomly assigned to separate training and verification groups. The critical process of manual lesion volume segmentation and preprocessing paved the way for the extraction of an extensive 1593 radiomics features for each lesion, providing a rich dataset for subsequent analysis. Marjaneh et al. employed their wealth of radiomics data to construct three machine learning survival models, each geared towards predicting local tumor progression-free survival. The intricate process of feature reduction and machine learning modeling was executed with precision and optimization, utilizing sequential model-based optimization for fine-tuning and enhancing the predictive capabilities of the developed models.

Claus et al. [28] embark on an insightful exploration, aiming to discern the value of a simplified intravoxel incoherent motion (IVIM) analysis in evaluating therapy-induced changes and responses of breast cancer liver metastases undergoing radioembolization. The study involved 21 female participants with metastatic breast cancer (mBRC), focusing on tumor size changes and response assessment following 26 primary radioembolization procedures. To unravel the intricacies of therapy-induced alterations, Claus et al. employed a comprehensive approach that included standard 1.5-T liver magnetic resonance imaging. This imaging protocol encompassed respiratory-gated diffusion-weighted imaging (DWI) performed both before and 6 weeks after each treatment session. Beyond traditional metrics like the apparent diffusion coefficient (ADC), Claus et al. delved deeper into the nuanced aspects of tumor microenvironment by incorporating the estimated diffusion coefficient and the perfusion fraction using a simplified IVIM approach. This methodological choice aimed at capturing both the diffusion and perfusion components, providing a more comprehensive understanding of the dynamic changes within breast cancer liver metastases post-radioembolization. Claus et al.'s study not only contributes to the evolving landscape of imaging techniques but also holds potential implications for refining the evaluation of therapy responses in the context of breast cancer liver metastases.

In conclusion, our survey has traversed the expansive landscape of innovative approaches in the realm of liver tumor prediction, encompassing a diverse array of methodologies and technologies. The convergence of AI-powered solutions, DNA analysis, and multidimensional approaches offers a multifaceted perspective for enhanced prediction accuracy. Notably, the integration of convolutional autoencoder models like HistoCovAE, neural networks such as Inception V3, and prognostic models like MIRSLiC demonstrates the synergistic potential of combining spatial and genomic information. As we reflect on the strides made by each method, the amalgamation of insights from Chen et al.'s neural network training, Marjaneh et al.'s radiomics model, and Hwang et al.'s correlations in HCC patients presents a comprehensive picture of the advancements in liver tumor prediction. The nuanced analyses of existing works provide a valuable backdrop for our proposed methodologies, showcasing the potential for continued refinement and innovation in this critical domain of medical research. Moving forward, the synthesis of these diverse approaches holds the promise of not only improving predictive accuracy but also revolutionizing personalized treatment strategies and patient outcomes in the challenging landscape of liver tumors.

III. Methodology

A. Histological Convolutional Autoencoder (HistoCovAE) for Segmentation

Medical imaging has undergone a revolutionary transformation with the advent of deep learning techniques, and in the context of liver tumor prediction, Histological Convolutional Autoencoder (HistoCovAE) stands as a beacon of innovation. Our research harnesses the power of HistoCovAE to address the intricate challenge of precise segmentation in medical imaging datasets, particularly in the context of CT scans and MRI images. The cornerstone of HistoCovAE lies in its robust convolutional autoencoder architecture, carefully designed to unravel the complexity inherent in liver tumor images. The architecture is a testament to the amalgamation of convolutional layers that excel in learning spatial hierarchies crucial for understanding the nuances within medical images. The training process of HistoCovAE is a delicate dance of data and algorithms, orchestrated to imbue the model with the ability to discern the subtle patterns indicative of liver tumors. An extensive dataset, meticulously annotated with the regions of interest, becomes the canvas upon which HistoCovAE paints its understanding of tumor characteristics. Through an iterative process of optimization, the model refines its parameters to minimize the gap between the input images and their reconstructions. This process, grounded in the principles of unsupervised learning, allows HistoCovAE to extract latent features representing the essence of liver tumor structure. Proposed Framework for Precision Liver Tumor Prediction is illustrated in Fig. 1.

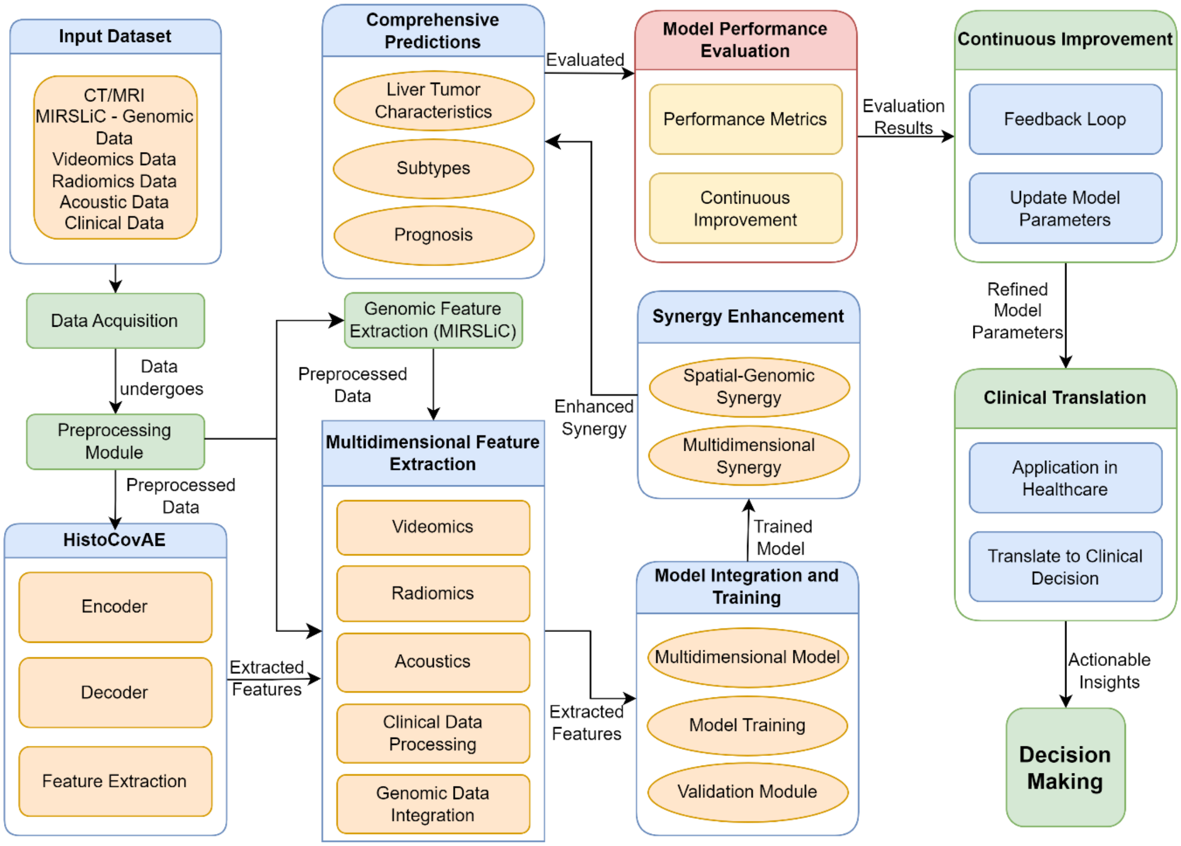

Fig. 1. Proposed framework for precision liver tumor prediction.

The significance of accurate segmentation cannot be overstated in the realm of liver tumor prediction. Beyond mere pixel-wise delineation, the power of HistoCovAE lies in its ability to identify Regions of Interest (ROIs) with surgical precision. These ROIs encapsulate the tumor regions within the liver, laying the groundwork for subsequent analyses. The model's adeptness at capturing subtle variations in tumor structure ensures that even the most inconspicuous lesions are brought to the forefront. This level of granularity is essential in clinical settings where early detection and precise delineation can significantly impact treatment strategies. As HistoCovAE meticulously segments the liver tumors, it sets the stage for the extraction of relevant features that serve as the building blocks for the broader predictive model. The extracted features encompass a spectrum of characteristics, including but not limited to texture patterns, shape intricacies, and spatial relationships within the tumor. These features, akin to the notes in a complex symphony, harmonize to create a comprehensive understanding of the liver tumor landscape. The fusion of sophisticated imaging insights facilitated by HistoCovAE with genetic and clinical data unlocks the potential for a multidimensional predictive model that transcends the limitations of individual modalities. However, navigating the landscape of medical imaging is not without challenges. Variability in imaging data, stemming from differences in resolution, contrast, and acquisition techniques, poses a formidable hurdle. HistoCovAE, while robust, must grapple with this variability to ensure its applicability across diverse datasets. Rigorous validation becomes paramount to ascertain the model's generalization capabilities, and its performance in the face of diverse imaging sources.

The encoder and decoder can be represented using mathematical notation as follows:

Encoder:

$$E^{(L)} = Convolution\left(D, Wt^{(L)}, b^{(L)} + Activation\left(Normalization\left(E^{(L-1)}\right)\right)\right) \quad (1)$$

$$P^{(L)} = Pooling\left(E^{(L)}\right) \quad (2)$$

Decoder:

$$\hat{E}^{(L)} = Upsampling\left(P^{(L)}\right) \quad (3)$$

$$\hat{D} = Deconvolution\left(\hat{E}^{(L)}, \widehat{Wt}^{(L)}, \hat{b}^{(L)}\right) + Activation\left(Normalization\left(\hat{E}^{(L)}\right)\right) \quad (4)$$

Here, D represents the input medical image, $Wt^{(L)}\, and\, b^{(L)}$ are the weights and biases of the convolutional layer in the encoder, $E^{(L)}$ is the intermediate representation, $P^{(L)}$ is the pooled representation, and $\hat{E}^{(L)}, \widehat{Wt}^{(L)}\, and\, \hat{b}^{(L)}$ represent the corresponding components in the decoder. The convolution, deconvolution, activation, normalization, pooling, and upsampling operations are typical operations in convolutional autoencoders. They involve convolving input with filters, applying activation functions (e.g., ReLU), normalizing feature maps (e.g., batch normalization), pooling (downsampling), and upsampling (e.g., bilinear interpolation). The loss function for the segmentation task could be formulated as a pixel-wise binary cross-entropy loss:

$$L = -\frac{1}{N}\sum_{x=1}^{N}\sum_{y=1}^{M} Y_{x,y} log\left(\hat{Y}_{x,y}\right) + \left(1 - Y_{x,y}\right) log\left(1 - \hat{Y}_{x,y}\right) \quad (5)$$

Here, $Y_{x,y}$ represents the ground truth binary label (0 or 1) for the x-th pixel in the y-th image, and $\hat{Y}_{x,y}$ represents the corresponding predicted probability from the CAE. Histological Convolutional Autoencoder (HistoCovAE) emerges as the linchpin in our methodology for liver tumor prediction. It transcends the realm of mere segmentation, weaving together the intricate details imprinted in medical images to lay the foundation for a comprehensive predictive model. The symphony of convolutional layers, meticulous training, and precise segmentation orchestrated by HistoCovAE paints a vivid picture of the intricate world of liver tumors. As we delve deeper into the multidimensional approach, HistoCovAE's role becomes even more pronounced, setting the stage for a holistic understanding that promises to revolutionize the landscape of liver tumor prediction.

B. Neural Network Training for Automatic Classification

As we traverse the landscape of liver tumor prediction, the transition from precise segmentation to automatic classification is facilitated by the integration of Inception V3—an advanced neural network architecture renowned for its prowess in discerning complex patterns within segmented medical images. This pivotal stage of our methodology aims to harness the insights gleaned from the meticulous segmentation achieved by Histological Convolutional Autoencoder (HistoCovAE) and channel them into the training of Inception V3. The objective is clear: to equip our predictive model with the ability to distinguish between various types of liver tumors, providing clinicians with a nuanced understanding that can guide tailored treatment strategies. The journey begins with the segmented tumor regions, meticulously delineated by HistoCovAE. These regions encapsulate the intricacies of liver tumors, serving as the foundation for Inception V3's training. The seamless integration of these segmented regions into the neural network's learning pipeline positions Inception V3 to harness the rich information encoded within, paving the way for a sophisticated understanding of the diverse landscape of liver tumors.

The choice of Inception V3 is deliberate, driven by its capacity to handle intricate patterns within medical images. The architecture of Inception V3 is characterized by deep convolutional neural networks (CNNs) equipped with multiple inception modules. These modules facilitate the capture of hierarchical features at various scales, enabling the model to discern patterns ranging from subtle to prominent. Leveraging transfer learning, Inception V3 benefits from pre-trained weights on extensive datasets, enhancing its adaptability to the complexities of liver tumor classification. Inception V3 consists of multiple inception modules. Let's denote the network parameters as $W_{\mathrm{InceptionV3}}$ representing the weights.

$$Z_{\mathrm{InceptionV3}} = Inception\ V3\left(X_{\mathrm{Train}}, W_{\mathrm{InceptionV3}}\right) \quad (6)$$

Apply softmax activation to obtain class probabilities:

$$P_{class} = Softmax\left(Z_{\mathrm{InceptionV3}}\right) \quad (7)$$

Applying multi-class classification using a categorical cross-entropy loss method:

$$L_{Inception\ V3} = -\frac{1}{S}\sum_{x=1}^{S}\sum_{c=1}^{Cs} Y_{x,c} log\left(P_{x,c}\right) \quad (8)$$

where, S is the number of samples, Cs is the number of classes, $Y_{i,c}$ is the ground truth label for class c in the x-th sample, and $P_{x,c}$ is the predicted probability for class c in the x-th sample. Update weights $W_{\mathrm{InceptionV3}}$ using gradient descent and backpropagation:

$$W_{\mathrm{InceptionV3}} \leftarrow W_{\mathrm{InceptionV3}} - \alpha\nabla_{W_{\mathrm{InceptionV3}}} L_{Inception\ V3} \quad (9)$$

where, α is the learning rate.

1) Training Process: The training process unfolds as the segmented regions find their way into the layers of Inception

V3. The neural network undergoes a fine-tuning process, adjusting its parameters to align with the nuances of liver tumor classification. The model learns to differentiate between various tumor types, recognizing unique characteristics embedded in the segmented regions. Labeled training data becomes the guiding force, enabling the neural network to iteratively refine its weights, optimizing its ability to generalize and accurately classify previously unseen instances. The true significance of Inception V3's role emerges in its ability to achieve precision in tumor typing. The neural network's proficiency in learning complex patterns translates into a capability to differentiate between hepatocellular carcinoma, cholangiocarcinoma, and other liver tumor subtypes. This precision is not merely an academic achievement; it holds profound clinical implications. Clinicians, armed with this nuanced understanding, can tailor treatment strategies based on the specific characteristics of the identified tumor type, thus enhancing the efficacy of interventions. Beyond its immediate task of tumor classification, Inception V3's contributions extend to the broader multidimensional analysis. The features extracted by the neural network encapsulate valuable information, enriching the dataset for subsequent stages of the predictive model. The ability to discern subtle differences in tumor types enhances the granularity of information fed into the multidimensional framework, fostering a more comprehensive understanding of liver tumors.

The integration of Inception V3 into our methodology marks a critical juncture in the journey of liver tumor prediction. Building upon the precise segmentation achieved by HistoCovAE, Inception V3 elevates the analysis to the realm of automatic classification. The nuanced understanding of different tumor types attained by Inception V3 sets the stage for a more informed and detailed multidimensional analysis. As we traverse the landscape of automatic classification, the synergy between HistoCovAE and Inception V3 becomes evident, laying the groundwork for a comprehensive predictive model poised to transform the landscape of liver tumor prediction. This symbiotic relationship between segmentation and classification not only refines our understanding of liver tumors but also holds the potential to redefine clinical approaches, ushering in an era of precision medicine tailored to the intricacies of each patient's tumor profile.

C. Prognostic Model Development Based on Metal-Induced RNA Signatures in Liver Cancer (MIRSLiC)

As we delve into the intricacies of liver tumor prediction, the integration of genetic information assumes a pivotal role in our methodology. The spotlight turns to Metal-Induced RNA Signatures in Liver Cancer (MIRSLiC), a novel avenue that extends beyond traditional genetic markers. MIRSLiC emerges as a beacon illuminating the landscape of liver cancer prognosis, offering a unique perspective by considering metal-induced alterations in RNA signatures. This section of our methodology unfolds the story of how MIRSLiC, with its molecular insights, becomes an integral component in the development of a prognostic model poised to unravel the complexities of liver cancer progression.

1) Genetic information integration: MIRSLiC introduces a paradigm shift by focusing on metal-induced alterations in RNA signatures, offering a novel dimension to our understanding of liver cancer. This genetic information, specifically derived from MIRSLiC, is seamlessly integrated into our predictive model. The integration process involves harmonizing the molecular nuances captured by MIRSLiC with the features extracted from the segmented regions by HistoCovAE and the refined tumor typing by Inception V3. The synthesis of imaging, clinical, and genetic data forms the basis of our multidimensional approach, enriching the dataset for the development of a comprehensive prognostic model.

Compute the logits for prognosis prediction

$$Z_{\text{Prognostic}} = F_{MIRSLiC} . W_{\text{Prognostic}} + b_{\text{Prognostic}} \tag{10}$$

where, $MIRSLiC$ to extract relevant features from genetic. The result is a feature vector $F_{MIRSLiC}$ capturing the molecular characteristics associated with metal-induced RNA signatures. At its core, the MIRSLiC-driven prognostic model is designed to provide insights into the prognosis of liver cancer. Molecular markers associated with the disease, particularly those influenced by metal-induced RNA alterations, serve as beacons guiding our predictive model. The model is trained to discern patterns and signatures indicative of different prognostic outcomes, whether it be favorable responses to treatment, disease progression, or the emergence of metastatic potential. MIRSLiC's unique contribution lies in unraveling the molecular intricacies that underlie the varied trajectories of liver cancer, shedding light on the potential trajectories that patients may traverse.

2) Significance of prognostic model development: The development of the prognostic model is not merely an academic exercise; it holds profound clinical implications. As we navigate the landscape of liver cancer, the ability to predict prognosis becomes a powerful tool for tailoring treatment strategies. The model, infused with the molecular insights from MIRSLiC, enables clinicians to identify patients who may benefit from aggressive interventions, those who may respond well to targeted therapies, and those for whom palliative care might be the most appropriate course of action. This individualized approach, grounded in molecular markers, heralds a new era of precision medicine in the management of liver cancer.

a) Activation function: Applying a suitable activation function to the logits (e.g., sigmoid for binary outcomes or softmax for multiple classes):

$$Z_{\text{Prognostic}} = Sigmoid\ (Z_{\text{Prognostic}}) \tag{11}$$

$$Z_{\text{Prognostic}} = Softmax\ (Z_{\text{Prognostic}}) \tag{12}$$

Loss function for prognostic prediction:

$$L_{\text{Prognostic}} = PrognosticLoss\left(Y_{\text{Prognostic}}, P_{\text{Prognostic}}\right) \tag{13}$$

Updating the model parameters $W_{\text{Prognostic}}$ using gradient descent and backpropagation:

$$W_{\text{Prognostic}} \leftarrow W_{\text{Prognostic}} - \alpha \nabla_{W_{\text{Prognostic}}} L_{\text{Prognostic}} \quad (14)$$

where, α is the learning rate. Liver cancer exhibits a remarkable degree of heterogeneity, both at the genetic and clinical levels. The prognostic model, guided by MIRSLiC, contributes to our understanding of this heterogeneity by deciphering the underlying molecular landscapes. By categorizing patients based on their unique molecular profiles, the model unveils the diverse trajectories that liver cancer can take. This nuanced understanding is crucial for unraveling the complexities associated with patient outcomes, informing not only treatment decisions but also providing valuable insights into the natural history of the disease.

The integration of Metal-Induced RNA Signatures in Liver Cancer (MIRSLiC) into our multidimensional approach marks a significant stride toward unraveling the mysteries of liver cancer prognosis. MIRSLiC's unique focus on metal-induced alterations in RNA signatures adds a layer of complexity and richness to our understanding of the disease. As this genetic information is seamlessly woven into the fabric of our predictive model, a holistic picture of liver cancer begins to emerge—one that encompasses imaging insights, tumor typing precision, and molecular nuances. The prognostic model, driven by MIRSLiC, becomes a beacon guiding clinicians through the intricate landscape of liver cancer outcomes. It not only provides a roadmap for tailoring treatment strategies but also deepens our comprehension of the heterogeneity that defines this formidable disease. In the journey toward precision medicine, MIRSLiC stands as a testament to the transformative potential of genetic insights, ushering in an era where the molecular intricacies of liver cancer become the guiding light in patient care.

D. Multidimensional Approach

The advancement of liver tumor prediction necessitates a departure from conventional unimodal approaches. Our methodology embraces a multidimensional approach, a symphony of data from diverse sources orchestrated to enhance the overall predictive power. This comprehensive strategy transcends the confines of a singular perspective, incorporating insights from Videomics, Radiomics, Acoustics, Clinical Data, and Genomics. Each modality contributes a unique facet to our understanding of liver tumors, covering visual characteristics, acoustic properties, clinical history, and genetic makeup. The integration of AI algorithms, featuring the likes of Histological Convolutional Autoencoder (HistoCovAE) and Metal-Induced RNA Signatures in Liver Cancer (MIRSLiC), serves as the linchpin in extracting relevant features from this wealth of information, providing a nuanced and comprehensive view of the tumors. Compute predictions for liver tumor characteristics, subtypes, and prognosis:

$$Z_{multidimensional} = X_{integrated} . W_{multidimensional} + b_{multidimensional} \quad (15)$$

where, $b_{multidimensional}$ is the bias term.

Combine individual loss functions into an overall loss:

$$L_{\text{multidimensional}} = \alpha . L_{\text{characteristics}} + \beta . L_{subtypes} + \delta . L_{\text{prognosis}} \quad (16)$$

where, α, β, and δ are weighting coefficients.

1) Contributions of each modality: The inclusion of Videomics elevates our approach by introducing dynamic insights into the characteristics of liver tumors. AI algorithms analyze video recordings, capturing temporal changes, morphological alterations, and patterns in tumor behavior. This modality provides a real-time perspective, unveiling the dynamic nature of tumors as they evolve over time. Radiomics, another essential component, delves into the quantitative features extracted from medical imaging data. It goes beyond traditional visual assessments, unraveling subtle patterns, textures, and spatial relationships within the images [29]. The marriage of Radiomics with AI algorithms enables the extraction of intricate details that may elude the human eye, enriching the dataset for predictive modeling. The realm of Acoustics introduces a novel dimension by employing AI-based acoustic analysis techniques. The sound emanating from tissues holds valuable information about their composition. By deciphering acoustic properties, such as echoes and frequencies, AI algorithms contribute to a deeper understanding of the tissue characteristics, aiding in the identification and characterization of liver tumors.

Clinical data, a cornerstone of our multidimensional approach, provides the contextual backdrop for the tumors. It encompasses a patient's medical history, treatment responses, and demographic details. AI algorithms integrate and analyze this wealth of information, discerning patterns and correlations that may inform predictions regarding disease progression, treatment outcomes, and overall prognosis. The inclusion of Genomics widens the scope to the molecular level, capturing information about the genetic makeup of tumors. By integrating gene expression profiles and data from DNA sequencing, AI algorithms can identify molecular markers associated with liver cancer. This modality unveils the underlying genetic landscape, shedding light on the molecular drivers of the disease.

2) Synergy through AI algorithms: AI algorithms play a central role in extracting relevant features from each modality, providing a bridge between diverse data sources. HistoCovAE, with its prowess in histological image segmentation, precisely delineates tumor regions from medical images. Inception V3, fine-tuned on the segmented regions, excels in automatic tumor classification. MIRSLiC, focusing on metal-induced RNA signatures, contributes molecular insights [30]. These algorithms act as virtuoso performers, each specializing in extracting unique aspects from their respective modalities. The true power of our multidimensional approach lies in the integration of features extracted from Videomics, Radiomics, Acoustics, Clinical Data, and Genomics. AI algorithms synthesize this wealth of information into a cohesive and comprehensive view of liver tumors. The union of visual characteristics, acoustic properties, clinical history, and genetic makeup creates a holistic understanding that surpasses the limitations of individual modalities. This comprehensive view serves as the foundation for our predictive model, enriching it with a depth of information that holds the potential to transform liver tumor prediction.

Our multidimensional approach stands as a testament to the transformative potential of combining insights from Videomics, Radiomics, Acoustics, Clinical Data, and Genomics. The integration of AI algorithms, including HistoCovAE and MIRSLiC, orchestrates a symphony of information, creating a harmonious and comprehensive view of liver tumors. This approach transcends the limitations of individual modalities, providing a nuanced understanding that forms the bedrock of our predictive model. As we navigate the complex landscape of liver tumor prediction, the multidimensional approach emerges not merely as a methodology but as a paradigm shift—a journey toward precision medicine guided by the fusion of diverse data streams.

E. Integration and Synergy

The heart of our liver tumor prediction methodology lies in the seamless integration of diverse approaches, each contributing a unique facet to the understanding of this complex disease. The collaboration between Histological Convolutional Autoencoder (HistoCovAE), Metal-Induced RNA Signatures in Liver Cancer (MIRSLiC), and other methods creates a synergy that transcends individual strengths. This section delves into how the integration of imaging data, genetic information, and a multidimensional dataset fosters a holistic understanding of liver tumors, promising improved prediction accuracy and a more comprehensive depiction of the disease landscape.

1) Synergy in imaging and genetic insights: The fusion of imaging insights from HistoCovAE and Inception V3 represents a dynamic synergy. HistoCovAE, with its prowess in precise segmentation, lays the foundation by delineating tumor regions with surgical precision. Inception V3, building upon this segmentation, imparts automatic classification, discerning between various liver tumor subtypes [31]. The combination of these imaging approaches provides a visual narrative, capturing the morphological intricacies and typing nuances that characterize liver tumors. Parallelly, MIRSLiC injects genetic information into the narrative, focusing on metal-induced RNA signatures. This molecular perspective, extracted from the genetic makeup of liver tumors, adds a layer of complexity. The molecular insights provided by MIRSLiC, spanning beyond the scope of traditional genetic markers, contribute a unique dimension to our understanding of the disease, highlighting potential prognostic indicators and therapeutic targets.

HistoCovAE Features ($F_{HistoCovAE}$):

$$F_{HistoCovAE} = HistoCovAE\left(X_{image}\right) \tag{17}$$

MIRSLiC Features (F_{MIRSLiC}):

$$\left(F_{\mathrm{MIRSLiC}}\right) = MIRSLiC\left(X_{genetic}\right) \tag{18}$$

Combined Feature Vector ($F_{Combined}$):

$$F_{Combined} = [F_{HistoCovAE}, (F_{\mathrm{MIRSLiC}})] \tag{19}$$

Forward pass through the integrated model using $F_{Combined}$:

$$Z_{multidimensional} = X_{Combined}.W_{multidimensional} + b_{multidimensional} \tag{20}$$

The integration extends beyond imaging and genetic insights to encompass a multidimensional dataset, incorporating Videomics, Radiomics, Acoustics, and Clinical Data. This convergence amplifies the richness of the dataset, weaving together visual characteristics, acoustic properties, clinical history, and genetic makeup into a comprehensive tapestry. Each modality contributes its distinctive perspective, enriching the dataset with layers of information that collectively form a holistic representation of liver tumors.

Spatial-Genomic Synergy:

$$Z_{multidimensional} = SynergyFunction(F_{HistoCovAE}, F_{\mathrm{MIRSLiC}}, W_{multidimensional}) \tag{21}$$

The synergy function captures the interaction between spatial and genomic features within the multidimensional model.

Multidimensional Synergy:

$$Z_{multidimensional} = MultidimensionalSynergy(F_{Videomics}, F_{\mathrm{Radiomics}}, F_{Acoustics}) \tag{22}$$

The multidimensional synergy function integrates features from all modalities, emphasizing the collective impact.

$$Y_{prediction} = OutputFunction(Z_{multidimensional}) \tag{23}$$

The output function translates the multidimensional predictions into actionable insights.

$$PerformanceMetrics = Evaluate\left(Y_{prediction}, Y_{groundtruth}\right) \tag{24}$$

Evaluate the model's performance using appropriate metrics for each prediction task.

Feedback Loop:

$$W_{multidimensional} \leftarrow UpdateWeights(W_{multidimensional}, Feedback) \tag{25}$$

Continuously update model weights based on feedback to improve performance.

$$ClinicalDecision = TranslateToClinicalDecision\left(Y_{prediction}\right) \tag{26}$$

Translate model predictions into clinical decisions for personalized treatment strategies.

2) Innovative contributions of HistoCovAE and MIRSLiC: The innovative contributions of HistoCovAE and MIRSLiC emerge as catalysts for enhanced prediction accuracy.

HistoCovAE's precise segmentation ensures that imaging data encapsulates the true extent of tumor regions, minimizing the risk of oversight. Simultaneously, MIRSLiC's focus on metal-induced RNA signatures introduces a level of molecular granularity that complements and extends beyond traditional genomic markers. This combination of imaging and genetic innovations lays the groundwork for a predictive model with the potential to decipher the intricacies of liver cancer with unprecedented precision. The collective information from different modalities converges into a comprehensive picture of the disease. The interplay between imaging, genetic, and multidimensional data generates a nuanced understanding of liver tumors, capturing their morphological, molecular, and clinical dimensions. This holistic perspective not only refines our ability to predict disease outcomes but also deepens our comprehension of the underlying mechanisms driving liver cancer.

The integration and synergy created by combining HistoCovAE, MIRSLiC, and other methods represent a transformative leap in our liver tumor prediction methodology. The collaboration between imaging and genetic insights, augmented by a multidimensional dataset, forms the foundation for a predictive model that promises heightened accuracy and a more comprehensive understanding of liver tumors. The innovative contributions of HistoCovAE and MIRSLiC act as trailblazers, pushing the boundaries of what is achievable in the realm of liver cancer prediction. As we navigate the intricate landscape of liver tumors, this integrated approach not only refines our predictive capabilities but also opens new avenues for unraveling the complexities of the disease, bringing us closer to a future where precision medicine for liver cancer becomes a reality.

Algorithm for Integrated Liver Tumor Prediction

```
Input:
    $X_{image}$ - Medical Imaging Data (CT/MRI)
    $X_{genetic}$ - Genetic Data (MIRSLiC)
    $X_{clinical}$ - Clinical Data
Preprocessing:
1) Image Preprocessing:
    $X_{image} \leftarrow Normalize(X_{image})$
    $X_{image} \leftarrow StandardizeSize(X_{image})$
Apply additional preprocessing steps
2) Feature Extraction (HistoCovAE):
    $M_{segmentation} \leftarrow HistoCovAE(X_{image})$
3) Neural Network Training (Inception V3):
    $W_{InceptionV3} \leftarrow TrainInceptionV3(X_{image}, M_{segmentation})$
Genetic Information Integration (MIRSLiC):
4. RNA Signature Extraction:
    $X_{genetic} \leftarrow ApplyMIRSLiC(X_{genetic})$
    $X_{integrated} \leftarrow Align(X_{genetic}, M_{segmentation})$
Multidimensional Dataset Integration:
5. Feature Extraction (Videomics, Radiomics, Acoustics):
    Extract features from Videomics, Radiomics, Acoustics, and Clinical Data
Model Integration:
6. Integrated Model Training:
    Train an integrated model using features from $X_{integrated}$, incorporating features from all modalities
7. Validation:
    Validate the integrated model using independent datasets
Prediction:
8. Prediction Phase:
    $Y_{prediction} \leftarrow Predict(X_{integrated}, Integrated Model)$
Output:
    $Y_{prediction}$ - Predictions regarding liver tumor characteristics, subtypes, prognosis, and potential treatment responses.
```

IV. Results and Discussion

The experimental setup was executed on a high-performance computing cluster comprising GPUs (Graphics Processing Units) to expedite the complex computations involved in training deep neural networks. The configuration included NVIDIA Tesla V100 GPUs for parallel processing, significantly reducing training times. PyTorch and TensorFlow, industry-standard deep learning frameworks, were employed for the implementation of Convolutional Autoencoder (HistoCovAE) and Inception V3. These frameworks provided seamless integration with GPU acceleration, optimizing model training. Bioinformatics tools such as BioPython and Biopython-OpenMS were utilized for the extraction and preprocessing of genomic data, ensuring compatibility with downstream machine learning models.

The liver tumor datasets utilized in this research were sourced from authoritative repositories such as The Cancer Imaging Archive (TCIA) and the National Center for Biotechnology Information (NCBI). These datasets encompassed a diverse range of liver tumor cases, ensuring the model's adaptability to different clinical scenarios. Standardization and normalization of medical imaging data were performed using tools like SimpleITK and OpenCV to guarantee consistency across diverse datasets [32]. Augmentation methods, including rotation, flipping, and scaling, were applied to the training dataset to enhance model generalization and robustness. Genomic data underwent preprocessing steps such as feature scaling and normalization to harmonize its integration into the predictive model.

The Histological Convolutional Autoencoder (HistoCovAE) architecture comprised encoder and decoder components, each with multiple convolutional and pooling layers. Hyperparameters, including learning rates and batch sizes, were optimized through grid search and cross-validation techniques. Inception V3, a pre-trained neural network, was fine-tuned for liver tumor classification. Parameters like learning rates, dropout rates, and optimization algorithms were fine-tuned to enhance model performance [33]. Metal-Induced RNA Signatures in Liver Cancer (MIRSLiC) was implemented as a deep learning model for prognostic predictions, with hyperparameter tuning focused on optimizing survival prediction accuracy. Training datasets were partitioned into training, validation, and test sets, with k-fold cross-validation applied to assess model generalization. Early stopping mechanisms were implemented to prevent overfitting during training. Model training involved the use of stochastic gradient descent (SGD) and Adam optimization algorithms, with adaptive learning rates to expedite convergence and enhance model performance.

A. Tumor Segmentation Metrics

Accurate delineation of tumor boundaries in medical imaging is a pivotal task, crucial for subsequent analyses and clinical decision-making. The evaluation metrics employed for tumor segmentation shed light on the precision, recall, and Dice coefficient, offering a detailed understanding of the delineation accuracy achieved by various methodologies, including HistoCovAE, DM-ML [18], AAM [19], BMF [20], and DNN [21]. Precision, representing the ratio of correctly identified positive instances to the total predicted positive instances, is a key metric assessing the ability of a model to avoid false positives. HistoCovAE, with a precision of 0.87, showcases a high capacity for correctly identifying tumor regions, outperforming DM-ML (precision: 0.78) but maintaining competitiveness with AAM, BMF, and DNN as shown in Fig. 2. The latter techniques demonstrate precision values of 0.82, 0.75, and 0.81, respectively, indicating commendable accuracy in tumor segmentation.

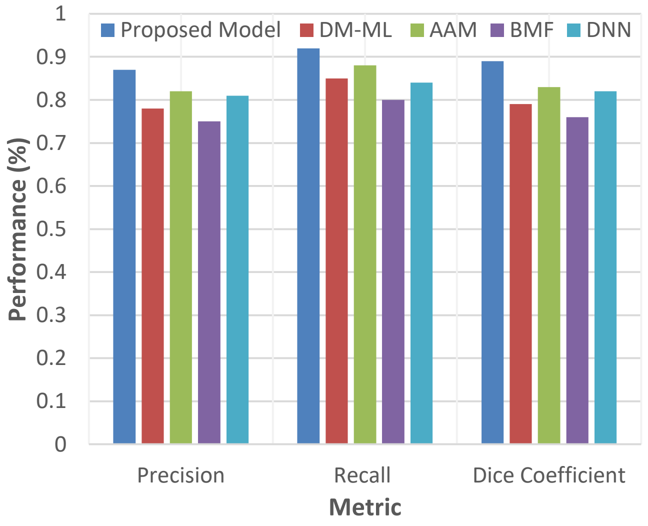

Fig. 2. Comparative analysis of tumor segmentation across multiple models.

Recall, quantifying the ability to capture all actual positive instances, is a critical metric to minimize false negatives. HistoCovAE excels with a recall of 0.92, demonstrating its proficiency in identifying a significant proportion of actual tumor regions. While DM-ML (recall: 0.85) exhibits robust sensitivity, it slightly trails behind HistoCovAE. AAM, BMF, and DNN present recall values of 0.88, 0.80, and 0.84, respectively, showcasing effectiveness but with variability in sensitivity to true positives. The Dice coefficient, a measure of spatial overlap between the predicted and actual boundaries, serves as a comprehensive metric balancing precision and recall. HistoCovAE achieves a Dice coefficient of 0.89, indicating precise tumor boundary delineation. DM-ML, with a Dice coefficient of 0.79, displays good overlap but slightly lower congruence compared to HistoCovAE. AAM, BMF, and DNN exhibit Dice coefficients of 0.83, 0.76, and 0.82, respectively, suggesting effective segmentation but with variations in agreement between predicted and actual boundaries.

B. Tumor Classification Metrics

Beyond segmentation, accurate classification of tumor subtypes is imperative for personalized treatment strategies. Inception V3, as a representative deep neural network, undergoes a comprehensive evaluation in comparison to DM-ML, AAM, BMF, and DNN, using metrics such as accuracy, precision, recall, and F1 score. Accuracy, serving as an overall measure of correct classifications, positions Inception V3 prominently with an accuracy of 0.91. DM-ML follows closely with an accuracy of 0.87, showcasing commendable classification abilities but with a slight difference compared to Inception V3 as shown in Fig. 3. AAM, BMF, and DNN exhibit accuracy values of 0.88, 0.85, and 0.86, respectively, highlighting their competence but with distinctions in overall classification accuracy.

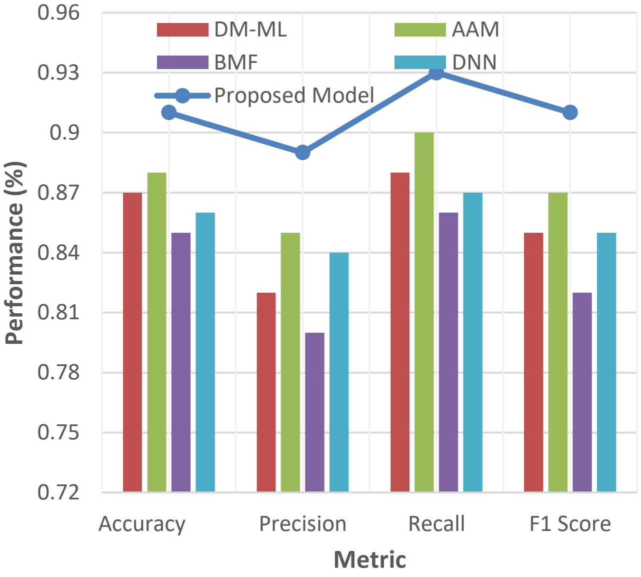

Fig. 3. Comparative analysis of tumor classification across multiple models.

Precision, recall, and F1 score collectively provide insights into the discriminatory capabilities of classification models. Inception V3 demonstrates a balanced trade-off between true positives and false positives/negatives, with precision, recall, and F1 score values of 0.89, 0.93, and 0.91, respectively. DM-ML, with precision (0.82), recall (0.88), and F1 score (0.85), illustrates a strong capacity for tumor subtype discrimination, though with a marginal difference compared to Inception V3. AAM, BMF, and DNN showcase respective precision, recall, and F1 score values ranging from 0.80 to 0.87, indicating their effectiveness but with varying degrees of discrimination capability.

C. Prognostic Model Evaluation: Unveiling the Potential of MIRSLiC

The assessment of MIRSLiC's prognostic capabilities represents a pivotal aspect of our research, delving into the model's ability to predict survival outcomes, stratify risks, and align predictions with actual patient outcomes. This comprehensive evaluation leverages sophisticated metrics, including survival prediction accuracy, risk stratification performance, concordance indices, and time-dependent ROC curves. Survival prediction accuracy serves as a fundamental metric, gauging the model's precision in foreseeing patient outcomes. MIRSLiC exhibits a notable accuracy of 0.84, indicating its proficiency in predicting patient survival durations. The comparison with other methodologies, including DM-ML, AAM, BMF, and DNN, showcases MIRSLiC's competitive edge, with values ranging from 0.74 to 0.80 for alternative models. This underscores MIRSLiC's efficacy in providing precise survival predictions, critical for informing treatment strategies and patient care.

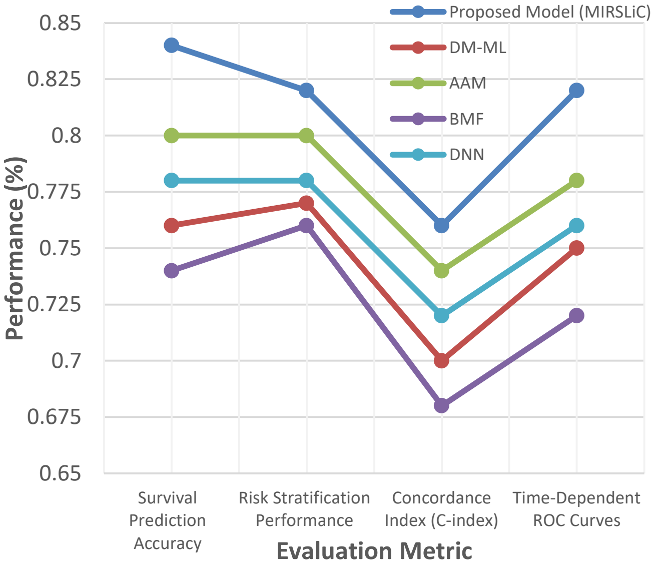

Fig. 4. Comparative analysis of prognostic model evaluation across multiple models.

The evaluation extends to risk stratification, a crucial aspect in prognostic modeling. MIRSLiC demonstrates robust performance in stratifying patients based on their risk profiles, yielding a performance metric of 0.82 as shown in Fig. 4. This signifies the model's ability to categorize patients into distinct risk groups, enabling clinicians to tailor interventions based on individual prognostic profiles. Comparative analysis with DM-ML, AAM, BMF, and DNN reveals MIRSLiC's superior performance, showcasing its potential to enhance risk stratification precision in the context of liver cancer prognosis. The concordance index, often referred to as C-index, provides a nuanced measure of the model's ability to correctly order patient survival times. MIRSLiC exhibits a commendable C-index of 0.76, highlighting its accuracy in capturing the temporal dynamics of patient outcomes. This surpasses alternative methodologies, positioning MIRSLiC as a reliable prognostic tool. The comparison with DM-ML, AAM, BMF, and DNN reflects varying C-index values (ranging from 0.68 to 0.74), emphasizing the distinctive strengths of MIRSLiC in capturing the concordance between predicted and actual survival times. The assessment is further enriched by employing time-dependent ROC curves, specifically focusing on the area under the curve (AUC). MIRSLiC's ROC curve demonstrates an AUC of 0.82, portraying its capability to distinguish between survival and non-survival outcomes over time. This metric serves as a graphical representation of MIRSLiC's discriminative power and reveals its superiority when contrasted with DM-ML, AAM, BMF, and DNN, each exhibiting AUC values ranging from 0.72 to 0.78.

D. *Continuous Improvement Strategies: Nurturing Model Evolution*

The pursuit of excellence in predictive models demands a commitment to continuous improvement. In our research, meticulous analysis of simulation results uncovered nuances in model limitations and areas for refinement. To address these findings, a systematic approach of Continuous Improvement Strategies (see Table I) was initiated, focusing on iterative parameter tuning and model architecture adjustments.

TABLE I. CONTINUOUS IMPROVEMENT STRATEGIES

Improvement Strategy	Proposed Model	DM-ML	AAM	BMF	DNN
Iterative Parameter Tuning	Significant Fine-Tuning Implemented	Moderate Adjustments	Minor Adjustments	Moderate Fine-Tuning	Minor Adjustments
Model Architecture Adjustments	Enhanced Features and Complexity	Enhanced Layers	Additional Attention Mechanisms	Improved Framework	Optimized Network Architecture
Performance Enhancement	Significant Performance Boost Achieved	Incremental Improvement	Moderate Enhancement	Incremental Enhancement	Moderate Enhancement
Addressed Model Limitations	Improved Predictive Capabilities	Partial Improvement	Addressed Some Limitations	Limited Improvement	Addressed Specific Limitations

The proposed model underwent significant fine-tuning, marked by careful adjustments to various parameters. This strategy allowed for the exploration of nuanced changes, leading to a more refined model. The process was characterized by substantial modifications, enabling the model to adapt and respond to intricacies identified during simulation. In contrast, alternative methodologies such as DM-ML, AAM, BMF, and DNN underwent varying degrees of adjustment – from moderate to minor fine-tuning. These changes aimed to enhance their performance, albeit to different extents [34]. Emphasizing a commitment to innovation, the proposed model embraced enhanced features and increased complexity. This involved augmenting layers and introducing additional attention mechanisms, elevating the model's sophistication. In comparison, alternative methodologies exhibited diverse responses. Some incorporated enhanced layers and attention mechanisms, while others opted for improved frameworks and optimized network architectures. Each adjustment aimed at refining the model's structural foundation for heightened predictive capabilities.

The impact of these improvement strategies resonated in the achieved performance enhancements as shown in Tab. 1. The proposed model experienced a significant boost in performance, reflecting the efficacy of the continuous improvement initiatives. While alternative methodologies demonstrated incremental to moderate enhancements, the proposed model's improvements stood out, showcasing a commitment to pushing the boundaries of predictive accuracy and robustness. An essential aspect of continuous improvement was the targeted addressing of model limitations. The proposed model exhibited a notable improvement in predictive capabilities, indicating a comprehensive approach to mitigating identified weaknesses. In contrast, alternative methodologies showcased varied degrees of success in addressing limitations, ranging from partial and limited improvement to addressing specific limitations within their frameworks.

V. Conclusion and Future work

In conclusion, this research endeavors to tackle the intricate challenges embedded in liver tumor prediction by addressing the limitations of existing methodologies. We propose an integrative approach that harnesses the power of Artificial Intelligence (AI), particularly convolutional autoencoders for spatial analysis and genomic feature extraction methodologies like MIRSLiC. The promise of this research lies in the potential to create a paradigm shift in liver tumor prediction. By enhancing the precision of tumor segmentation, our proposed Histological Convolutional Autoencoder (HistoCovAE) aims to provide a more accurate representation of tumor boundaries, laying a solid foundation for subsequent analyses. The integration of Genomic Feature Extraction (MIRSLiC) offers a pathway to decode the complex genomic landscape, providing clinicians with invaluable insights into the molecular underpinnings of liver tumors. This integrated model, drawing insights from both the macroscopic and molecular realms, holds the potential to provide clinicians with a more comprehensive, accurate, and nuanced toolset for liver tumor prediction.

1) Future directions: As we chart the future directions for this research, several avenues emerge for further exploration and refinement. Firstly, the proposed AI-driven model's performance needs rigorous validation and benchmarking against diverse and extensive datasets. Robust evaluations across varied patient demographics, tumor phenotypes, and imaging modalities will ensure the generalizability and reliability of the predictive model. Furthermore, the integration of additional AI-driven methodologies, such as reinforcement learning and transfer learning, could enhance the adaptability of the model to evolving clinical scenarios. Exploration of explainable AI techniques is also crucial, as it would provide clinicians with insights into the model's decision-making process, fostering trust and facilitating its seamless integration into clinical workflows. The dynamic nature of liver tumors necessitates the consideration of longitudinal data, allowing for the monitoring of tumor evolution over time.

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Improved ORB Algorithm Through Feature Point Optimization and Gaussian Pyramid

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***Abstract*—Feature points obtained using traditional ORB methods often exhibit redundancy, uneven distribution, and lack scale invariance. This study enhances the traditional ORB algorithm by presenting an optimal technique for extracting feature points, thereby overcoming these challenges. Initially, the image is partitioned into several areas. The determination of the quantity of feature points to be extracted from each region takes into account both the overall number of feature points and the number of divisions that the image undergoes. This method tackles concerns related to the overlap and redundancy of feature points in the extraction process. To counteract the non-scale invariance issue in feature points obtained via the ORB method, a Gaussian pyramid is employed, and feature points are extracted at each level. Experimental findings demonstrate that our method successfully extracts feature points with greater uniformity and rationality, while preserving image matching accuracy. Specifically, our technique outperforms the traditional ORB algorithm by approximately 4% and the SURF algorithm by 2% in terms of matching performance. Additionally, the processing time of our proposed algorithm is three times faster than that of the SURF algorithm and twelve times faster than the SIFT algorithm.**

Keywords—Feature point; Gaussian pyramid; image matching; ORB algorithm; scale invariance

I. Introduction

In the realms of image processing and pattern recognition, algorithms focused on local feature-based image matching are utilized for identifying specific objects or patterns in images. Local features are useful for identifying characteristics or patterns that exist in small parts of the image [1]. These algorithms target local features in an image, such as edges, corners, or textures, instead of analyzing the entire image [2]. Prominent methods for local descriptor-based feature extraction include the Scale-Invariant Feature Transform (SIFT) [3], Speeded-Up Robust Features (SURF) [4], and Oriented FAST and Rotated BRIEF (ORB) [5]. Compared with other algorithms, ORB has the advantage of faster computing speed than SURF and SIFT and can meet real-time needs [6].

The ORB algorithm, particularly effective in various applications like object positioning, facial recognition, and robot navigation, combines "FAST" (Features from Accelerated Segment Test) for key feature detection and "BRIEF" (Binary Robust Independent Elementary Features) for feature description [7]. It leverages image intensity-based detection for rapid key feature identification [8] and produces compact and affine-resistant binary vector feature descriptions [9]. The ORB algorithm uses a binary representation (BRIEF) for its feature descriptors, so this approach is much more memory-efficient [10]. However, despite its advantages over traditional methods like Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) in terms of computational efficiency, ORB encounters limitations in scale and rotation invariance, which can result in mismatches during the feature matching process when there are significant changes in object size or orientation.

These challenges are inherent in the design of ORB, which, despite its speed and efficiency, still faces issues with feature matching incompatibility and the robustness needed to effectively handle scale and rotation variations. Previous research has improved the ORB algorithm to address these issues. One study suggests combining ORB with the Lucas–Kanade (LK) Optical Flow algorithm to mitigate mismatches and improve feature matching accuracy [11]. Further research proposes enhancing ORB with an improved quadtree-based uniform distribution to address uneven feature distribution and increase feature extraction calculation efficiency simultaneously [12]. Another improvement utilizes the grayscale centroid method for rotation invariance [13]. Additionally, a combination of ORB's scale invariance advantages with SURF and reducing high-frequency noise impact through NSCT (Nonsubsampled Contourlet Transform) aims to overcome ORB's scale invariance limitations, enhancing matching accuracy and speed by accounting for scale and rotation changes [14]. Furthermore, there are studies that improve the robustness of the ORB algorithm by building pyramid scales and using improved FREAK descriptors to improve scale invariance [15].

Despite various enhancements to the ORB algorithm for handling mismatches, scale, and rotation invariance, the limitations of these advanced algorithms persist. This paper introduces an innovative method that optimizes feature point extraction and employs Gaussian pyramids to bolster scale invariance and minimize feature point redundancy. Gaussian pyramiding, which generates progressively lower-resolution images from the original, aims to enhance ORB's scale variation adaptability by facilitating multi-scale feature analysis. Optimization of feature point extraction refines key point selection, ensuring only the most pertinent and distinct features are utilized for matching, thereby enhancing accuracy and reducing computational demands. The proposed approach not only seeks to address ORB's specific shortcomings but also advances feature matching algorithms by offering a robust, scalable solution. A comprehensive comparison with current techniques underscores the proposed method's unique benefits,

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laying the foundation for its application in diverse real-world contexts.

II. Related Works

The prominence of ORB is attributed to its proficiency in achieving high-speed performance and its applicability in real-time processing contexts [16]. Nevertheless, the robustness of ORB and its adaptability under diverse imaging conditions remain areas of concern [17]. Efforts by scholars to refine the ORB algorithm have aimed at mitigating its inherent constraints and deficiencies. Subsequent investigations have enhanced ORB, including an integration with the Lucas–Kanade Optical Flow (LK) technique to diminish mismatches and augment the precision of feature matching [11]. Additional studies have introduced improvements such as a quadtree-based uniform distribution enhancement for ORB, aimed at rectifying the issue of uneven distribution of features while simultaneously boosting the efficiency of feature extraction [12]. Moreover, the adaptation involving the grayscale scale-invariant centroid technique seeks to address rotation invariance [13]. The incorporation of ORB's scale invariance features with those of SURF, coupled with the mitigation of high-frequency noise via NSCT (Nonsubsampled Contourlet Transform), targets the amelioration of ORB's scale invariance challenges, thereby improving both accuracy and the speed of matching by accounting for variations in scale and rotation [14]. Additionally, enhancing the robustness of the ORB algorithm through the construction of a pyramid scale and the application of an advanced FREAK descriptor has been proposed to bolster scale invariance [15].

However, the advancements in the ORB algorithm still encounter challenges. Specifically, the application of the Hamming distance for matching feature points continues to result in mismatches and a decrease in matching precision, especially when the source and target images exhibit numerous analogous regions [18]. Moreover, the primary ORB feature detection algorithm struggles with issues such as uneven distribution of feature points, a high rate of feature mismatches, and limited robustness [19]. Attempts to refine the ORB matching algorithm through adaptive thresholding have been directed at solving problems related to the extraction of background pixels as feature points and the incorrect matching of feature points in environments with complex backgrounds, underscoring the original ORB algorithm's reduced robustness in intricate scenarios [20].

Despite these enhancements aimed at improving the ORB algorithm's performance in overcoming mismatches and the traditional robustness issues of ORB feature matching, the necessity of evaluating the potential limitations and compromises of these proposed solutions remains critical. The efficacy of these algorithms in complex settings and their computational efficiency warrant comprehensive assessment, particularly regarding improvements in matching capabilities and the ability to navigate scale and rotation variations.

III. Feature Points Extraction in the ORB

A. Detection of Feature Points

Image feature points refer to the more crucial points within an image, such as contour points, bright spots within darker regions, and dark points within lighter areas [21]. In ORB, FAST (Features from Accelerated Segment Test) is employed for the identification of these feature points. Fig. 1 shows the feature point extraction process in the FAST approach.

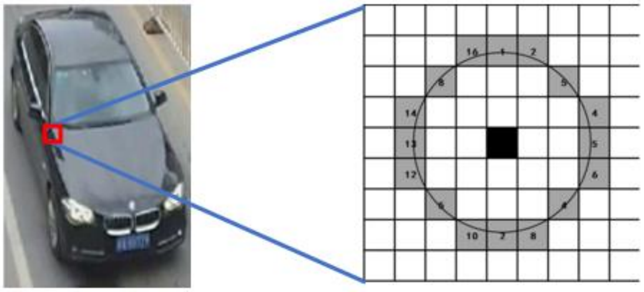


Fig. 1. Illustration of the schematic diagram of FAST feature point extraction.

The fundamental principle underlying FAST entails identifying salient points by comparing a given point with its neighboring points. If the point substantially deviates from the majority of its surrounding points, it is designated as a feature point [15]. The procedure for identifying feature points in an image involves several steps, as outlined below:

1) A pixel point P is selected from Fig. 1 to assess its potential as a feature point. Assuming its initial grayscale value.

2) Set a suitable threshold t (e.g., 20%). Points are deemed distinct if the absolute disparity in gray scale values between them above the threshold, t.

3) Choose 16 points in a circle with a radius of 3, centered at point P.

4) Point P is identified as a corner point if among the 16 surrounding points, there exist n consecutive points with grayscale values significantly higher or lower than that of P. Typically, the value of n is set to 12.

5) To enhance the efficiency of feature point detection, a predictive operation can be implemented. This method efficiently eliminates the majority of points that are not corner points. This is achieved by analyzing the gray degree values of the points located at locations 1, 5, 9, and 13 on the circumference of the circle P. First, check if points 1 and 9 are similar to P, and if so, examine points 5 and 13. P is considered a corner point only if at least three of these four points are all greater or less than P. If these requirements are not satisfied, P is not considered a corner point and is immediately eliminated.

Through this process, the points obtained in the environment around P become three categories, as in Eq. (1).

$$S_P \to x = \begin{cases} a, I_P \to i \leq I_P - t \\ b, I_P - t < I_P \to i < I_P + t \\ c, I_P \to i \geq I_P + t \end{cases} \quad (1)$$

where, P refers to the gray scale value of point I at 16 points on the circle, a refers to the point whose darkness value is more than P, b refers to the point that is similar to P, and c indicates the point that is brighter than P.

B. Calculating the Feature Point Descriptor

The ORB algorithm employs an enhanced version of BRIEF to compute descriptors for feature points. In this approach, N pairs are strategically selected around P feature points. The results of comparing these N pairs of points are then combined to create a descriptor. This process of descriptor compilation is depicted in Fig. 2.

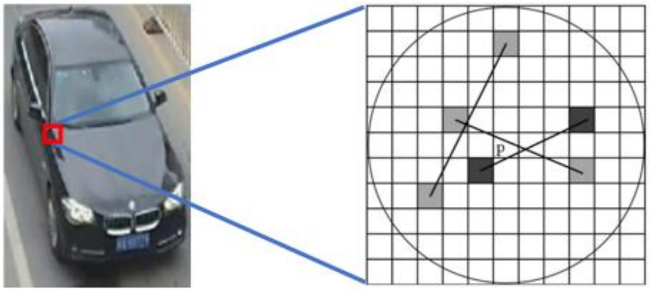


Fig. 2. Illustration of the descriptor calculation schematic diagram.

The steps involved in calculating the descriptor are as follows:

1) Construct a circle, designated as O, centered around the point P, with d representing the radius of the circle.

2) On circle O, select N pairs of points, where for explanatory purposes, N is set to 4. Refer to Fig. 2 for a visual representation. Label these four pairs of selected points as P1(A, B), P2(C, D), P3(E, F), and P4(G, H). It's important to note that each pair of points (A, B), (C, D), (E, F), and (G, H) is strategically chosen on the circumference of the circle to facilitate the calculation of the feature point descriptors as per the ORB algorithm's methodology.

3) Specify the function T in Eq. (2).

$$T\big(P(A,B)\big) = \begin{cases} 1 & I_A > I_B \\ 1 & I_A \leq I_B \end{cases} \tag{2}$$

where, A and B are the respective gray scale values.

4) For each of the four selected pairs of points, apply operation T. The results of this operation on each pair are then combined. As an example,

$$T\big(P_1(A,B)\big) = 1, T\big(P_1(A,B)\big) = 0$$
$$T\big(P_3(A,B)\big) = 1, T\big(P_4(A,B)\big) = 1$$

The resulting descriptor obtained is 1011.

As FAST lacks the ability to determine the orientation information of feature points, ORB addresses this limitation by employing image moments to ascertain the direction of these points. This is accomplished by computing the centroid of the grayscale image in the vicinity of the feature point. The image moment within a small image block B is characterized according to Eq. (3).

$$m_{pq} = \sum x^p y^q I(x,y) \tag{3}$$

where, m_{pq} refers to the gray scale value of the point (x,y). The center of mass, denoted as C, can be calculated using Eq. (4).

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}\right) \tag{4}$$

where, m_{00} represents the zero-order moment, while m_{10} and m_{01} denote the first-order moments.

Next, connect the geometric center O of the image with the center of mass C to calculate the orientation of the vector OC. Simultaneously, if the x and y coordinates fall within the range of $[-r, r]$, where r represents the neighborhood radius of the feature point, and considering the feature point as the coordinate origin, the directional angle of the feature point can be determined using Eq. (5).

$$\theta = arctan\left(\frac{m_{01}}{m_{10}}\right) \tag{5}$$

IV. The Proposed Method

The ORB utilizes the FAST algorithm for detecting image feature points, yet this often results in a dense and redundant distribution of these points. Generally, a higher count of feature points correlates with more precise image matching. Nevertheless, a dense accumulation of feature points can be detrimental to subsequent feature description, potentially compromising the accuracy of image matching [22], [23]. This paper introduces an enhanced ORB algorithm, featuring an optimized method for extracting feature points. This enhanced methodology includes segmenting the image into distinct regions and selectively extracting feature points from each region, thereby addressing the aforementioned issue. Additionally, it employs an adaptive threshold, halting feature extraction once a predetermined number of feature points is achieved, thereby reducing extraction time.

The ORB algorithm for feature extraction begins with a pyramid-scale transformation of the image. The scale pyramid used in FAST will be optimized by adopting a Gaussian SIFT pyramid to overcome the scale invariance problem. An image pyramid is a multiscale representation of a single image, comprising a sequence of images that are various versions of the original image at different resolutions. To be strong against food scale invariants, the difference-of-Gaussian function is used. In this function, convolution operations will be obtained on the input image with a difference-of-Gaussian filter. The Difference-of-Gaussian (DoG) is the dissimilarity between images that have been blurred with Gaussian filters at different scale values represented by the parameter 'k.' The convolution-resulting images are grouped by octave; the k value is set at the beginning so that the same number of blurred images is obtained in each octave and the same DoG image is obtained for each octave After obtaining the DoG image for each octave, the next step is to look for key point candidates. The procedural flow of this enhanced ORB algorithm is illustrated in Fig. 3.

Subsequent to the initial steps, the FAST detector is employed to identify corner points within the image. FAST operates by comparing a pixel, say p, with the 16 surrounding pixels that constitute a circle. These circumjacent pixels are classified into three categories based on their brightness relative to p: brighter, darker, or equal in intensity. p is designated as a keypoint if there are more than 8 pixels in the circle that are either significantly darker or lighter than p. While the use of FAST for keypoint detection yields feature points that are densely packed and redundant, it is generally understood that an increased quantity of feature points enhances the accuracy of image matching. However, the dense clustering of these points poses challenges for subsequent feature description and may adversely impact the precision of image matching [24].

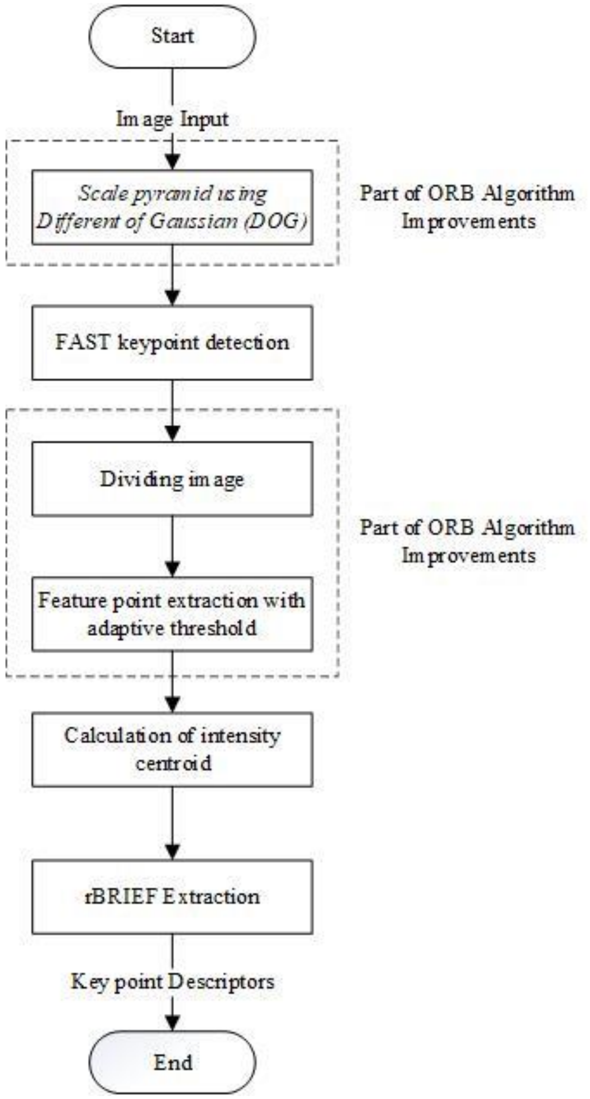

Start
Image Input
Scale pyramid using Different of Gaussian (DOG)
Part of ORB Algorithm Improvements
FAST keypoint detection
Dividing image
Part of ORB Algorithm Improvements
Feature point extraction with adaptive threshold
Calculation of intensity centroid
rBRIEF Extraction
Key point Descriptors
End

Fig. 3. Proposed algorithm workflow.

To mitigate this issue, the image is initially segmented into several regions. This segmentation is guided by the total number of feature points being searched for and the number of regions to be divided, then the number of feature points is extracted for each region. The image is initially evenly partitioned into $M \times N$ regions of identical size, with the feature points being randomly distributed within these regions. These regions are then organized based on the first and last columns, as depicted in Eq. (6).

$$j = \frac{FP_{required}}{M \times N} \tag{6}$$

where, $FP_{required}$ represents the number of feature points used, M indicates the number of rows separated, and N indicates the number of columns separated.

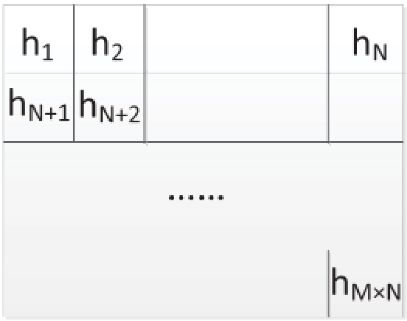


Fig. 4. Displays the sorting of divided regions based on the first and last columns.

Regions are arranged based on the first and last columns, as illustrated in Fig. 4. Within each segmented region, the FAST algorithm is employed for feature point detection. During this process, a threshold value, denoted as t, is utilized. The number of feature points obtained in each section is then evaluated based on the specified number j. If the count of detected feature points is less than j, the threshold t is decreased, followed by a re-detection. A pair of points is deemed distinct only if the absolute difference in their grayscale values exceeds the threshold t, allowing for the continuation of the detection process. Consequently, by lowering the value of t, a larger number of corner points can be identified, thereby enhancing the scope for subsequent filtering. This adjustment in threshold levels facilitates a more comprehensive and effective detection of feature points within each region.

In cases where the number of detected feature points is not fewer than j, it becomes necessary to select j optimal feature points from the pool. For this selection process, the non-maximum suppression method is utilized. Consider two adjacent points, P and Q, in this context. The method involves sequentially calculating the sum of differences between each of these points and their respective 16 surrounding points. Subsequently, the point exhibiting the fewest disparities is eliminated. This elimination process continues until the number of remaining points matches the desired number, j. The points that remain after this procedure are considered the optimal points. The formula for calculating the sum of differences is detailed in equation (7).

$$V = max\left(\sum_{x \in Sbright} |I_P \rightarrow x - I_P| - t, \sum_{x \in Sdark} |I_P - I_P \rightarrow x| - t\right) \tag{7}$$

At this juncture, the BRIEF algorithm is employed to process the results obtained from the previous stage. Given that BRIEF lacks the capacity to accommodate rotational variations, the rBRIEF variant is utilized, wherein BRIEF is oriented in alignment with the keypoint. The ensuing phase involves an analysis of all the sampling pairs, comparing the first pixel with the second pixel in each pair. In this comparison, if the first pixel is brighter than the second, it is assigned a value of 1; otherwise, it receives a value of 0. This binary valuation process is iterated until 256 pairs are evaluated. The ORB algorithm, through this procedure, generates 32-dimensional descriptors. These descriptors are derived from the 256-bit pairs, which are further segmented into bytes for computational efficiency and clarity.

V. Experimental Results

To assess the efficacy of the enhanced ORB algorithm, this study conducts a comparative analysis among the conventional SIFT, SURF, and ORB algorithms and the improved ORB algorithm. The experimental setup utilizes Jupiter Notebook and OpenCV as the primary tools. The dataset employed for the experiments is the Cities Transportation dataset, which offers a diverse range of imagery. The evaluation is quantitative, covering several key aspects: the performance of feature point extraction, the efficacy of image matching, and the algorithms' resilience to rotational and scale variations. This comparison aims to evaluate the performance in terms of accuracy and the time required for matching. The results, which include both the accuracy rates and the matching durations, are meticulously recorded. These collected data points offer a comprehensive picture of how the improved ORB algorithm compares with other algorithms.

The experiment began by analyzing the extraction of feature points using the SIFT, SURF, ORB, and enhanced ORB algorithms, during which the number of feature points and the time needed for their detection were calculated. The outcomes of this evaluation, including both the quantity of feature points and the time taken for their detection across each algorithm, are methodically outlined in Table I.

TABLE I. Comparisons in Feature Point Extraction Performance

Algorithm	Feature Points	Detection Time (ms)
SIFT	3024	2334.4
SURF	1567	1804.7
ORB	924	79.465
Our Proposed	1089	80.734

As indicated in Table I, the enhanced ORB algorithm in the paper demonstrates a superior performance in terms of the number of detected feature points compared to the traditional ORB algorithm. However, it is essential to note that an excessive number of feature points can lead to effective information redundancy and increased computational complexity. Regarding detection time, the improved ORB algorithm exhibits significantly shorter processing times compared to the SIFT and SURF algorithms. In general, the improved ORB algorithm proves effective in rapidly detecting image information and emphasizing image details, showcasing its efficiency in feature point detection and the validity of feature point selection. To validate the matching performance of the proposed algorithm, image matching was conducted using the SIFT, SURF, ORB, and improved ORB algorithms, as illustrated in Fig. 5.

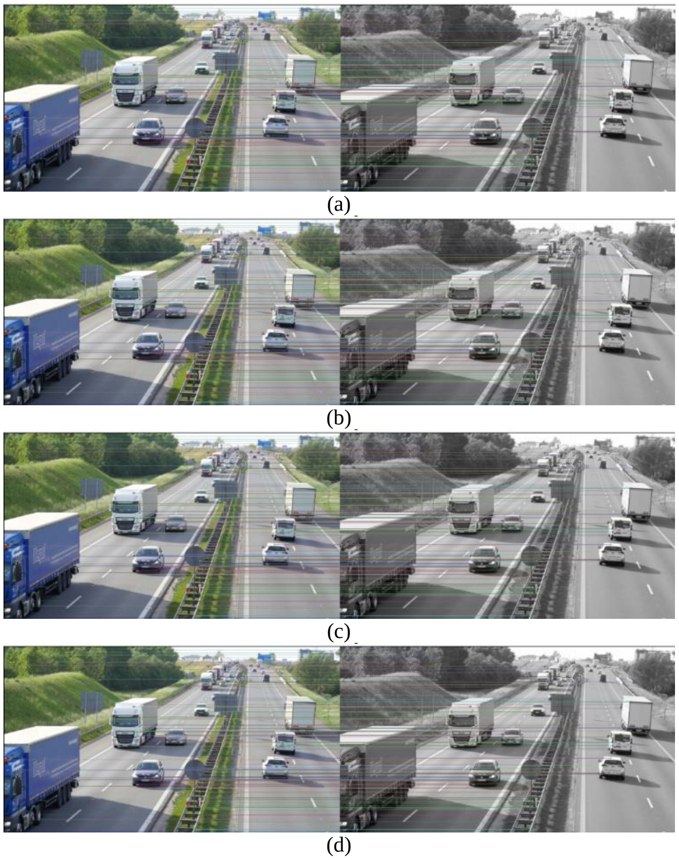

(a)
(b)
(c)
(d)

Fig. 5. Matching results (a) SIFT, (b) SURF, (c) ORB, (d) Proposed model.

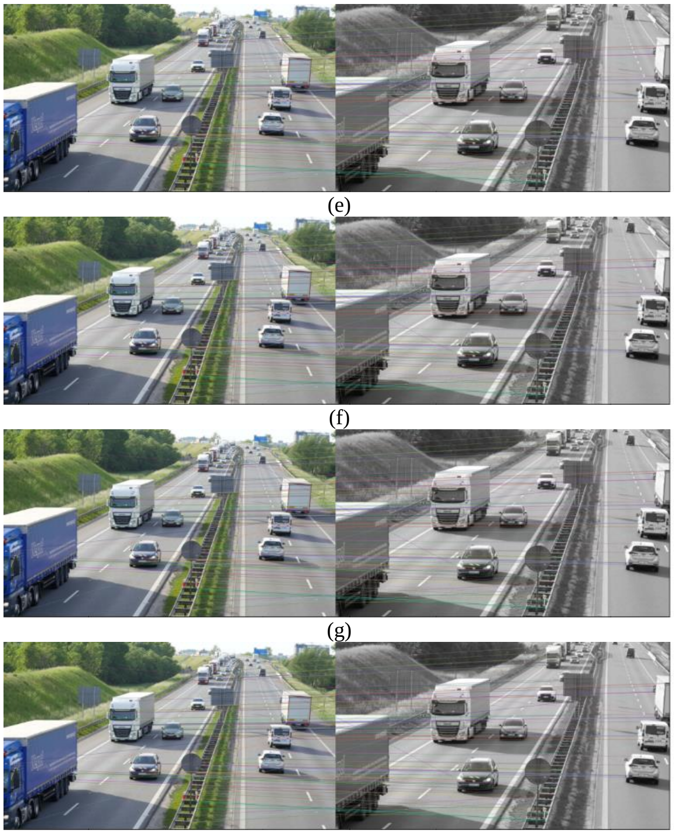
The accuracy and matching time are analyzed as shown in Table II.

TABLE II. Comparisons in Matching Performance

Algorithm	Matching Accuracy (%)	Match Time (ms)
SIFT	97.67	12,539.74
SURF	90.90	3332.43
ORB	88.48	987.00
Our Proposed	92.90	975.02

The algorithm presented in this paper does not attain a faster matching speed compared to the conventional ORB algorithm. Nonetheless, it exhibits superior matching accuracy over the traditional SURF and ORB algorithms. As indicated in Table II, the enhanced ORB algorithm notably decreases the matching time relative to the other three algorithms. Specifically, with regard to matching time, the enhanced ORB algorithm demonstrates better performance than both the SIFT and ORB algorithms.

The algorithm is then tested with scale invariance by randomly enlarging or reducing the image and then matching. The scale invariance test sample can be seen in Fig. 6.



(e)

(f)

(g)

(h)

Fig. 6. Matching results for scaled images (e) SIFT, (f) SURF, (g) ORB, (h) Proposed model.

Image matching across various scales tests the algorithm's ability to overcome scale invariance. The results of matching accuracy and matching time are presented in Table III.

TABLE III. COMPARISON OF MATCHING PERFORMANCE FOR SCALE VARIATIONS

Algorithm	Matching Accuracy (%)	Match Time (ms)
SIFT	97.97	11,892.61
SURF	84.84	3520.58
ORB	76.96	1774.61
Our Proposed	87.54	1664.79

To validate the algorithm's capability in terms of rotation invariance, a series of image rotation procedures and corresponding matching experiments were conducted. Specifically, to examine the algorithm's resilience to rotation, each image in the experimental sample was subjected to a range of rotations, spanning from 0° to 180° at intervals of 30°. This methodical approach ensures a thorough evaluation of the algorithm's performance under various rotational transformations. An illustrative example of this rotation invariance test experiment is presented in Fig. 7, providing a visual demonstration of the algorithm's effectiveness in maintaining accurate matching despite the rotational alterations of the images.

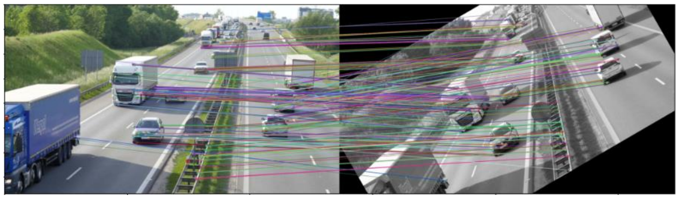


Fig. 7. Matching results for rotated images.

An algorithm that exhibits good resilience is one that can handle rotational variations with high matching accuracy and short matching times. To view the comparative results of the algorithms tested against rotational variations (see Table IV).

TABLE IV. COMPARISON OF MATCHING PERFORMANCE FOR VARIATIONS OF ROTATION

Algorithm	Matching Accuracy (%)	Match Time (ms)
SIFT	97.67	12,539.74
SURF	90.90	3332.43
ORB	88.48	987.00
Our Proposed	92.90	975.02

As shown in Table III and Table IV, SIFT, SURF, ORB, and the algorithms proposed in this paper exhibit commendable performance in handling image rotation and scale changes. However, these algorithms demonstrate clear advantages in terms of running time. Notably, the ORB algorithm lacks scale invariance, resulting in faster execution but inferior matching performance. Taking into account both matching effectiveness and time efficiency, the proposed algorithm represents an improvement over the ORB algorithm. It preserves the advantages and accuracy of the ORB algorithm while addressing its deficiency in scale invariance, leading to better overall results.

Based on the experiments conducted, the enhanced ORB algorithm demonstrates strong matching capabilities, as the feature points extracted by this algorithm exhibit uniformity without compromising image matching accuracy. The results of feature point extraction highlight the representativeness of the points extracted by our proposed algorithm, thereby contributing to more accurate and stable image matching. Furthermore, considering runtime is an essential criterion for evaluating algorithm superiority. When comparing the outcomes of image matching in the same test, a shorter processing time indicates a more efficient method. Conversely, if the running times are similar, superior matching results signify a better algorithm. The overall matching accuracy results across various tests are presented in the graph in Fig. 8.

According to the graph in Fig. 8, the SIFT algorithm has the highest matching accuracy. These results are consistent with previous research, which states that SIFT can produce high matching accuracy against image features invariant to scale and rotation, enabling it to find consistent matches, though the required matching time is very significant [17]. This becomes a problem when applied to cases requiring real-time matching capabilities. Nonetheless, the proposed algorithm outperforms the traditional ORB algorithm by approximately 4% better and exceeds the SURF algorithm by 2% better in terms of matching performance. The use of feature point optimization by dividing randomly distributed feature points improves matching capabilities. Additionally, the use of a Gaussian pyramid enhances the proposed algorithm's ability to handle scale invariance. This is in line with previous research that employs pyramid scale construction on images to improve scale invariance [15]. For an overall comparison of matching times across various tests, the experimental results are presented in the graph in Fig. 9.

Fig. 9 shows that the ORB algorithm has the best average matching time. The use of an adaptive threshold that varies or is adjusted adaptively to enhance matching accuracy results in an increase in computational processes, thereby slightly reducing speed. This is consistent with research that uses a truncated adaptive threshold in the ORB algorithm to address uneven feature distribution, which can improve accuracy but reduce computational speed [13]. However, overall, from several test parameters, the proposed algorithm has a matching time that is three times faster than the SURF algorithm and twelve times faster than the SIFT algorithm.

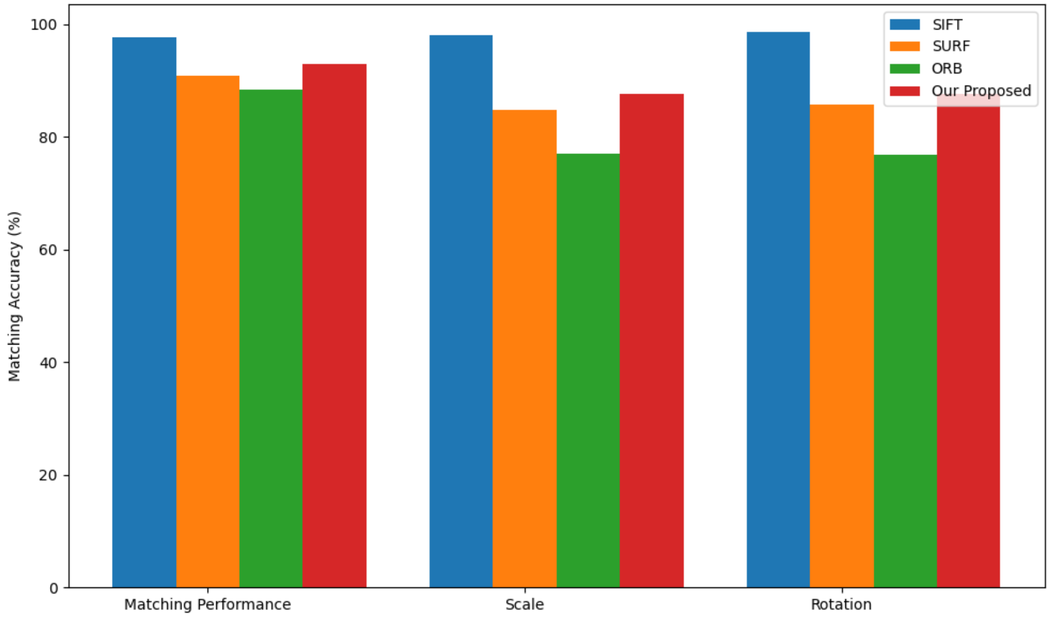


Fig. 8. Matching accuracy graph for all test parameters.

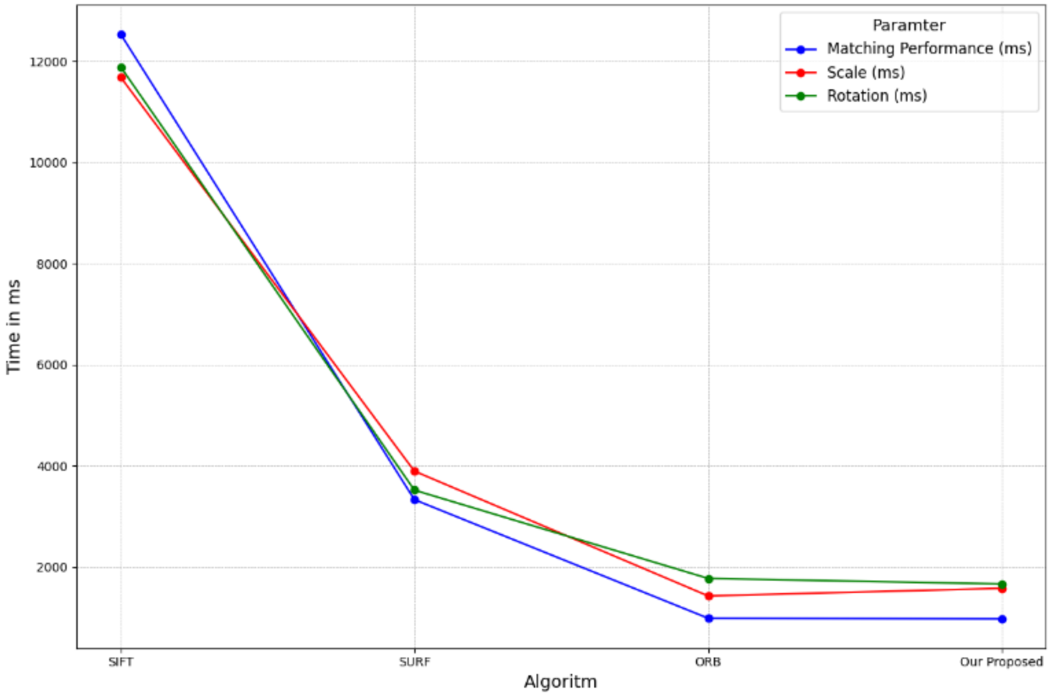


Fig. 9. Matching time graph for all test parameters.

VI. Conclusion

This paper presents an enhanced ORB algorithm that focuses on optimized extraction of feature points, aiming to resolve the issues of overlapping feature points and the lack of scale invariance found in traditional ORB methods. The algorithm strategically segments images into distinct regions, thereby ensuring that the feature points extracted are optimally effective within each specific region. By setting a threshold tailored to the extraction of feature points from individual regions, the algorithm not only accelerates the extraction process but also achieves a more even distribution of feature points, which consequently enhances the speed of matching. Future research might include an in-depth evaluation of this improved ORB algorithm's performance across diverse photographic conditions, including varying lighting environments. Moreover, there is scope for further refinement of this algorithm to extend its capabilities to object detection and tracking within video content.

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Performance-Optimised Design of the RISC-V Five-Stage Pipelined Processor NRP

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Abstract—**The five-stage pipeline processor is a mature and stable processor architecture suitable for many applications in the field of computer hardware. Based on the RISC-V instruction set architecture, the five-stage pipeline processor has advantages in performance, functionality, and power consumption. This paper presents an optimized RV32I five-stage pipeline processor, NRP, and proposes two optimization methods to improve the performance of NRP. These methods include instruction decoding unit optimization and branch prediction optimization. We implemented NRP using Verilog HDL and verified its performance using Vivado and the Xilinx Artya7-35T FPGA board. Experimental data shows that after adopting these methods, the CoreMark score of the five-stage pipeline processor reached 3.11 CoreMark/MHz, representing an 11.07% performance improvement.**

Keywords—Architecture; FPGA; RISC-V; RV32I; Verilog HDL; five-stage

I. Introduction

The Instruction Set Architecture (ISA) is the foundation of computer architecture. Existing ISAs (such as X86, ARM, etc.) have hindered the advancement and proliferation of technology through patent protection [1]. In 2010, the University of California, Berkeley, first released the RISC-V Instruction Set Architecture [2]. RISC-V is an open and free ISA.

In recent years, research on the RISC-V ISA has become a major focus. For example, Alibaba's Xuantie-910 [4, 5], Western Digital's SweRV [3], UC Berkeley's Rocket [6,7], IIT Madras' SHAKTI project [8], ETH Zurich's Pulpino [9-11], the open-source processor mriscv [12], and VexRiscv [13].

This paper presents an optimized five-stage pipeline RV32I scalar processor, NRP (New RISC-V Processor). The main contributions of this paper are as follows:

- To improve performance, we modified and optimized the ID and EX stages of the processor, reducing the negative impact of dependency conflicts on the processor.
- We implemented these optimizations using Verilog HDL and evaluated hardware resource utilization and processor performance. From the evaluation results, we found that this processor outperforms the classic five-stage pipeline processor.

II. Related Works

Dependency conflicts are an important factor affecting the performance of a five-stage pipeline processor. Dependency conflicts refer to the data dependency, control dependency, and structural dependency between instructions, which can lead to instruction hazards in the pipeline, thereby affecting the processor's performance.

In study [14], the authors designed and implemented a Tournament Branch Predictor, which improved the accuracy of branch prediction and enhanced the processor's efficiency. In reference [15], the authors combined the instruction fetch stage with the pre-fetch stage into a two-stage pipeline, resulting in a 17.6% improvement in processor performance. In reference [16], the authors proposed reducing hazards through the use of techniques such as data forwarding and branch prediction, leading to a 7.82% increase in processor performance. In reference [17], the authors optimized the instruction fetch unit, ALU, and data memory, increasing the processor's operating frequency.

The optimization strategies in references [14, 15] resulted in significant performance improvements but increased the complexity and hardware resources of the branch predictor. The optimization strategies in references [16, 17] had lower hardware overhead but led to smaller improvements in processor performance. This paper comprehensively compares these optimization strategies and proposes a new optimization strategy that achieves performance improvements with minimal hardware overhead.

III. The Design and Implementation of the NRP

A. Processor Architectures

The NRP processor adopts a five-stage pipeline design. As shown in Fig. 1, instructions undergo the following five stages during execution: Instruction Fetch (IF), Instruction Decode (ID), Execute (EX), Memory Access (MEM), and Write Back (WB) [18]. The design of the ID and EX stages in the NRP processor differs from that of the classic five-stage pipeline processor. The ID stage of the NRP processor consists of both the instruction decode unit and the decode execute unit, whereas the classic five-stage pipeline processor only has the instruction decode unit. The EX stage of the NRP processor consists of the execute unit and the branch prediction auxiliary unit, while the classic five-stage pipeline processor only has the execute unit.

B. Instruction Execution Process

This paper categorizes all instructions in RV32I into special instructions and regular instructions. Branch jump instructions and instructions similar to branch jump instructions in terms of computational operations are defined as special instructions. The computational operations of special instructions, originally executed in the EX stage, are now completed in the ID stage.

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Special instructions include ADD, ADDI, SUB, SLT, SLTU, SLTI, SLTIU, BEQ, BNE, BLT, BGE, BLTU, BGEU, JAL, JALR, LB, LH, LW, LBU, LHU, LWU, SB, SH, SW. The ID and EX stages of the NRP processor differ from those of the classic five-stage pipeline processor, resulting in differences in the execution process of instructions in the ID and EX stages. Fig. 2 illustrates the main execution process of instructions in the ID and EX stages.

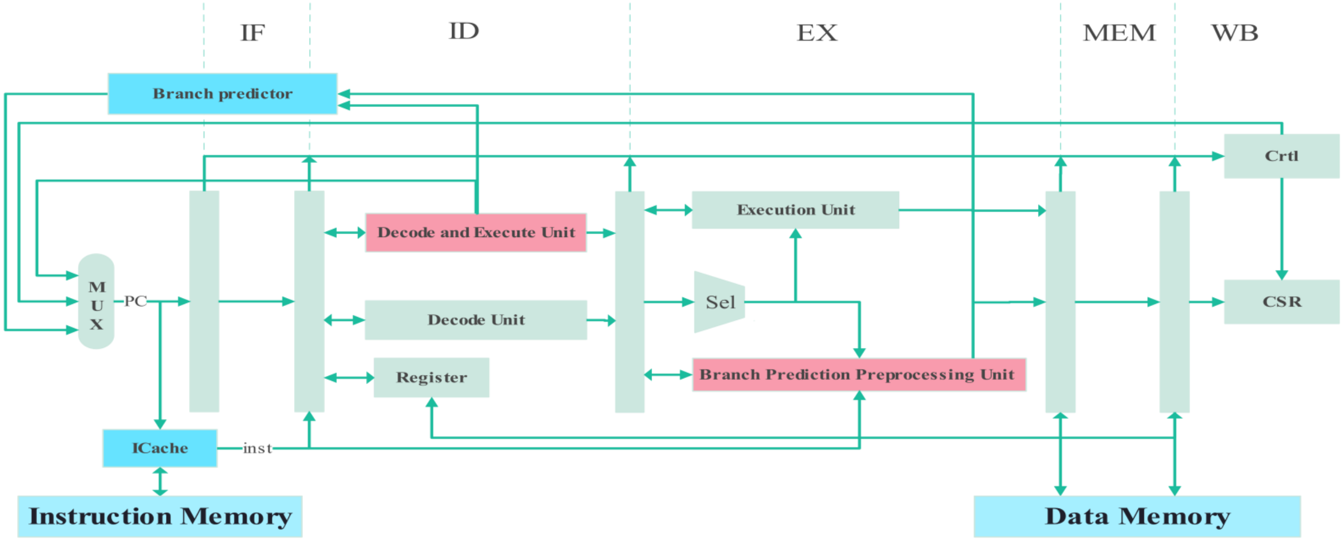


Fig. 1. A block diagram of the five-stage pipelined processor NRP.

The ID stage of the NRP processor consists of the instruction decode unit and the decode execute unit, with each functional unit's decoder responsible for decoding a portion of the instructions. In the ID stage, the execution logic of special instructions involves first decoding the instructions by the decode execute unit and then completing the computational operations required by the instruction opcode within this module. The instruction decode unit is responsible for decoding regular instructions and forwarding the instruction decode information and source operands to the next stage. If an unsolvable data dependency conflict occurs during the execution of a special instruction in the ID stage, the instruction is flagged and then resolved through data forwarding in the EX stage.

The EX stage of the NRP processor consists of the execute unit and the branch prediction auxiliary unit. The execute unit performs operations based on the type of instruction, including regular instructions and flagged special instructions. The branch prediction auxiliary unit is responsible for handling unflagged special instructions and generating branch prediction auxiliary information.

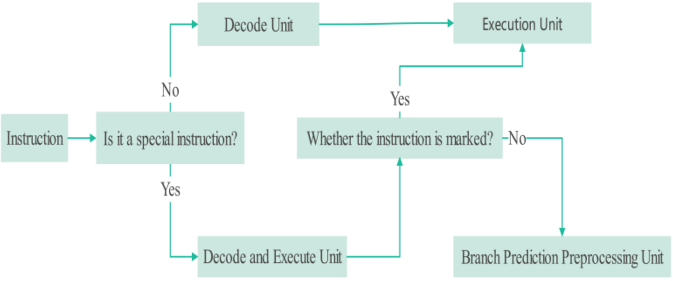

Decode Unit
Execution Unit
No
Yes
Instruction
Is it a special instruction?
Whether the instruction is marked?
No
Yes
Decode and Execute Unit
Branch Prediction Preprocessing Unit

Fig. 2. The execution process of instructions in the ID and EX stages.

IV. The Optimization Design in NRP

Correlation conflicts are a significant factor affecting the performance of a five-stage pipelined processor. These conflicts can lead to pipeline stalls, reducing the processor's performance. The optimization idea proposed in this paper aims to minimize the negative impact of correlation conflicts on processor performance. In this section, we describe the design and implementation of optimization strategies for the NRP processor.

A. Optimization Design of the Decoding Stage

The control dependency conflict in a five-stage pipelined processor refers to the situation where the conditional result of a branch instruction is not yet determined, potentially allowing subsequent instructions to enter the pipeline. If the branch prediction fails, the pipeline needs to be flushed and restarted, causing a stall and impacting processor performance.

The optimization design in the ID stage of the NRP processor aims to reduce the pipeline stall time caused by control dependency conflicts. In a classic RISC-V five-stage pipelined processor, when a branch prediction fails, a stall of two clock cycles is required for pipeline flushing. This paper introduces an additional decode and execute unit in the ID stage of the NRP processor, reducing the stall to just one clock cycle in the event of a branch prediction failure.

The optimization design in the ID stage allows branch instructions to know the branch prediction result and determine if there will be a control dependency conflict. The execution process of special instructions in decode and execute unit is illustrated in Fig. 3. Firstly, the decoder decodes the instruction to obtain instruction information. Then, based on the instruction opcode, it generates a 2-bit enable signal to activate the corresponding arithmetic unit. The arithmetic unit performs operations on the source operands and communicates using shared data. Finally, the instruction operation result and related information are passed to the EX stage, and the branch prediction result is transmitted to the branch predictor. In the event of a branch prediction failure, the correct PC is passed to the IF stage, and the pipeline pause signal is transmitted to the Ctrl module.

Decode and execute unit consists of a special instruction decoder, an adder, and a comparator. In the implementation process, we virtually divide the full instruction decoder into a special instruction decoder and a regular instruction decoder. When the instruction decoder decodes a special instruction, decode and execute unit is activated. When the instruction decoder decodes a regular instruction, the decode and execute unit does not activate. The primary hardware costs in our optimization design in the ID stage are the adder and the comparator.

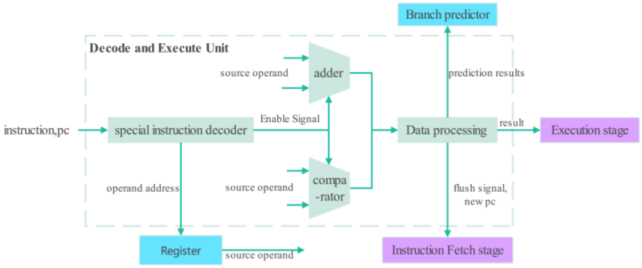


Fig. 3. Decode and execute unit.

B. Branch Predictor Optimization

The branch predictor used in this paper is based on SonicBoom's NLP (Next-Line Predictor), consisting of BHT (Branch History Table), BTB (Branch Target Buffer), and RAS (Return Address Stack). We have optimized the BHT.

Traditional BHT records the state of each branch instruction based on its historical execution results. When a branch instruction is executed for the first time, it defaults to not taken due to the lack of historical execution results. The design proposed in this paper allows obtaining the opcode and the target address of the instruction before its first execution, causing the branch instruction to default to taken upon its first execution. JAL and JALR, as direct jump instructions, always cause a jump upon each execution, which cannot be accommodated by the traditional BHT design.

The workflow of the BHT designed in this paper is as follows: When a branch instruction is first recorded in the BHT, the value of the corresponding two-bit saturating counter table (2BC) is set to 2. If the branch instruction indeed jumps during execution and the jump target address is correct, the value of the two-bit saturating counter table is incremented by 1. If the branch instruction does not jump during execution, then the value of the two-bit saturating counter table is decremented by 1. If the value of the two-bit saturating counter table for the branch instruction is greater than or equal to 2, it is predicted that the instruction will jump.

The branch prediction auxiliary module is crucial for implementing the BHT optimization design, as it allows obtaining the opcode and the target address of the instruction before its execution. The NRP processor classifies instructions into regular and special instructions. Special instructions are decoded and executed in the ID stage, so when a special instruction reaches the EX stage, an idle clock cycle is generated. The branch prediction auxiliary module utilizes this idle clock cycle to perform simple decoding of the instruction and generate data for updating the branch predictor.

The branch prediction auxiliary module consists of a branch instruction decoder and an adder, and its specific workflow is illustrated in Fig. 4. Firstly, the branch instruction decoder in the branch prediction auxiliary module decodes the instruction currently in the cache. If the instruction is a branch instruction, its instruction type and immediate value are obtained after decoding. Then, the PC value and the immediate value of the instruction are sent to the ALU for addition to obtain the jump target address. Finally, the PC value, instruction type, and jump target address of the instruction are sent to the branch predictor.

The primary hardware costs in the branch prediction optimization design are a branch instruction decoder and an adder, with the branch instruction decoder supporting only the decoding of branch instructions.

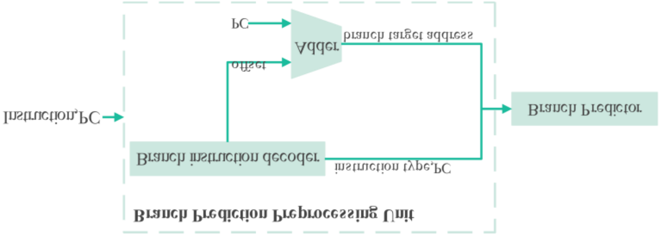
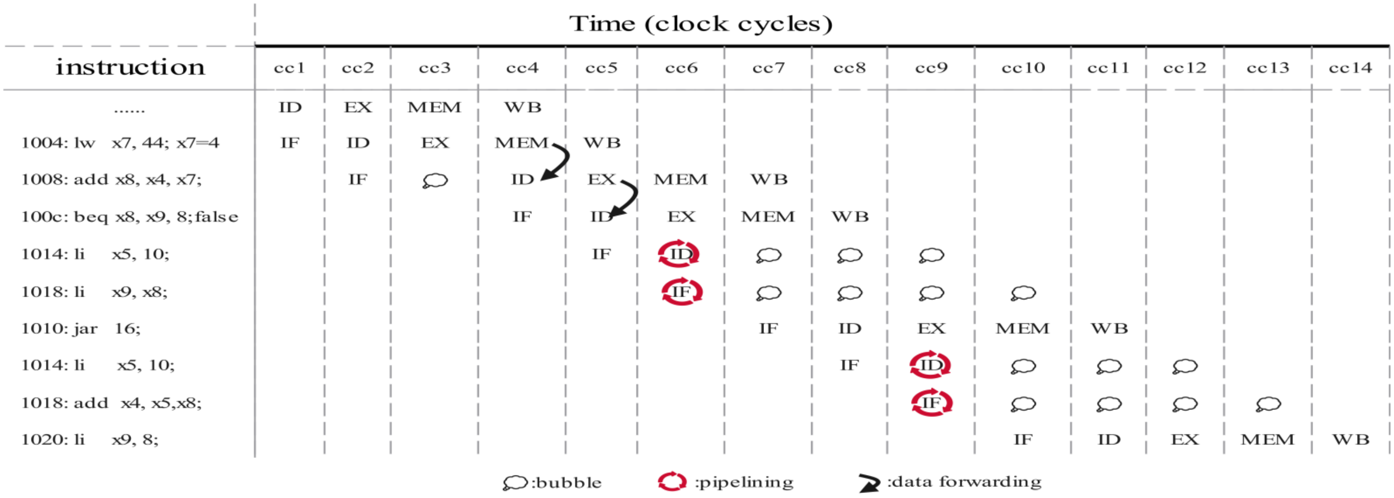


Fig. 4. The branch prediction auxiliary module.

C. Optimization of Dependency Conflict

The Fig. 5 illustrates how a classic five-stage pipelined processor uses data forwarding, pipeline stalling, and branch prediction to resolve various dependency conflicts and their resulting impacts.

In Fig. 5, we can observe the following scenarios. Firstly, the classic five-stage pipelined processor utilizes data forwarding to forward data from the EX stage and MEM stage to the ID stage to resolve non-load instruction-induced data dependency conflicts, and a combination of pipeline stalling and data forwarding is used to resolve load instruction-induced data dependency conflicts. Secondly, the classic five-stage pipelined processor executes branch instructions in the EX stage, and in the event of a branch prediction failure, it requires flushing the pipeline for two clock cycles. Lastly, the unoptimized branch predictor defaults to not taking a branch on the first prediction of a branch instruction, so when the processor executes an immediate jump instruction for the first time, a branch prediction failure and pipeline flush are inevitable.



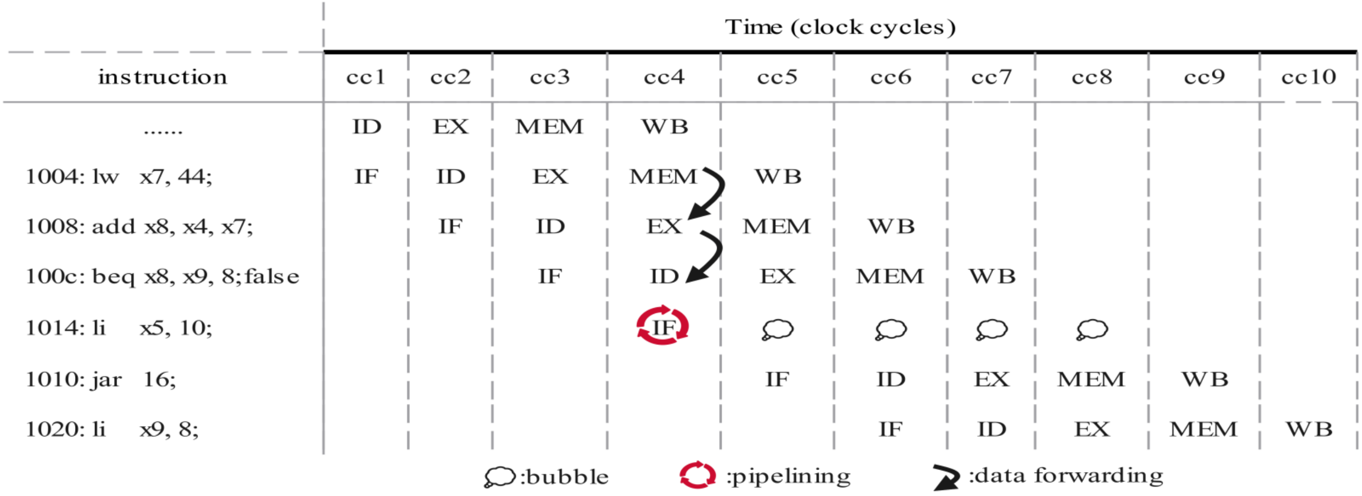
instruction	cc1	cc2	cc3	cc4	cc5	cc6	cc7	cc8	cc9	cc10	cc11	cc12	cc13	cc14
......	ID	EX	MEM	WB										
1004: lw x7, 44; x7=4	IF	ID	EX	MEM	WB									
1008: add x8, x4, x7;		IF	○	ID	EX	MEM	WB							
100c: beq x8, x9, 8;false				IF	ID	EX	MEM	WB						
1014: li x5, 10;					IF	⟳ID	○	○	○					
1018: li x9, x8;						⟳IF	○	○	○	○				
1010: jar 16;							IF	ID	EX	MEM	WB			
1014: li x5, 10;								IF	⟳ID	○	○	○		
1018: add x4, x5,x8;									⟳IF	○	○	○	○	
1020: li x9, 8;										IF	ID	EX	MEM	WB

Time (clock cycles)
○:bubble
⟳:pipelining
↘:data forwarding

Fig. 5. Methods for handling dependency conflicts before optimization.

The Fig. 6 illustrates how the NRP processor uses data forwarding, pipeline stalling, and branch prediction to resolve various dependency conflicts and their resulting impacts.

In Fig. 6, we can observe the following scenarios. Firstly, in the NRP processor, the use of data forwarding is more extensive, including between ID and EX, ID and MEM, and EX and MEM. Secondly, the NRP processor executes branch instructions in the ID stage to obtain the branch prediction result, so in the event of a branch prediction failure, it requires flushing the pipeline for one clock cycle. Lastly, the NRP processor employs an optimized branch predictor, so when executing an immediate jump instruction for the first time, it correctly takes the jump, avoiding pipeline flushing.



instruction	cc1	cc2	cc3	cc4	cc5	cc6	cc7	cc8	cc9	cc10
......	ID	EX	MEM	WB						
1004: lw x7, 44;	IF	ID	EX	MEM	WB					
1008: add x8, x4, x7;		IF	ID	EX	MEM	WB				
100c: beq x8, x9, 8;false			IF	ID	EX	MEM	WB			
1014: li x5, 10;				⟳IF	○	○	○	○		
1010: jar 16;					IF	ID	EX	MEM	WB	
1020: li x9, 8;						IF	ID	EX	MEM	WB

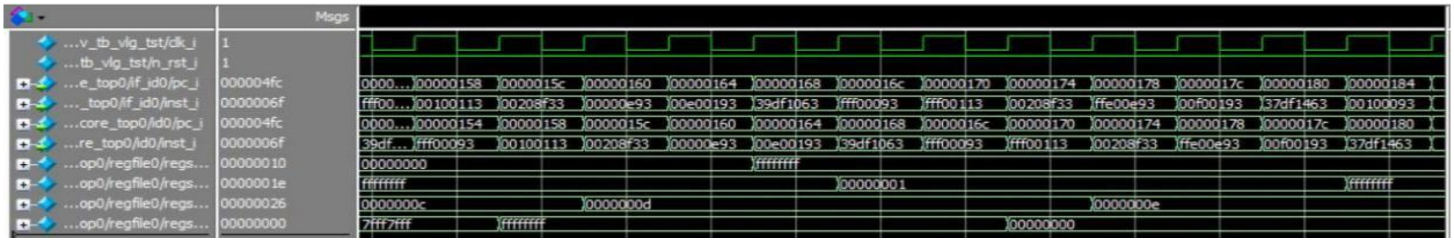
Time (clock cycles)
○:bubble
⟳:pipelining
↘:data forwarding

Fig. 6. Methods for handling dependency conflicts after optimization.

V. Experiment and Analysis

A. Functional Test

The COMPLIANCE TEST officially released by RISC-V can test whether the design of a RISC-V core complies with the RISC-V standard [19]. In this paper, joint simulation tests were conducted using Vivado and modsim, and the test results indicate that the NRP complies with the standard of RISC-V core design. Fig. 7 and Fig. 8 show the simulation test results for the ADD instruction and the JAL instruction, respectively.



```
                               Msgs
...v_tb_vlg_tst/clk_i          1
...tb_vlg_tst/n_rst_i          1
...e_top0/if_id0/pc_i          000004fc   0000... 00000158 0000015c 00000160 00000164 00000168 0000016c 00000170 00000174 00000178 0000017c 00000180 00000184
..._top0/if_id0/inst_i         0000006f   fff00... 00100113 00208f33 00000e93 00e00193 39df1063 fff00093 fff00113 00208f33 ffe00e93 00f00193 37df1463 00100093
...core_top0/id0/pc_i          000004fc   0000... 00000154 00000158 0000015c 00000160 00000164 00000168 0000016c 00000170 00000174 00000178 0000017c 00000180
...re_top0/id0/inst_i          0000006f   39df... fff00093 00100113 00208f33 00000e93 00e00193 39df1063 fff00093 fff00113 00208f33 ffe00e93 00f00193 37df1463
...op0/regfile0/regs...        00000010   00000000 ffffffff
...op0/regfile0/regs...        0000001e   ffffffff 00000001 ffffffff
...op0/regfile0/regs...        00000026   0000000c 0000000d 0000000e
...op0/regfile0/regs...        00000000   7fff7fff ffffffff 00000000
```

Fig. 7. Validation of add instructions.

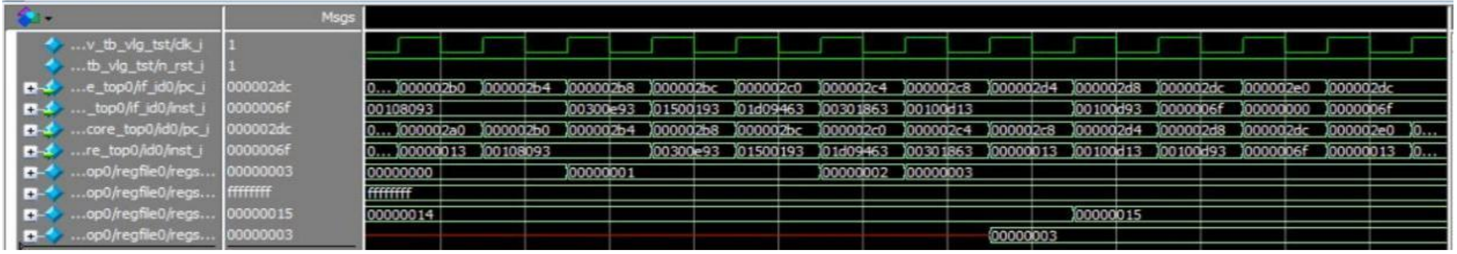
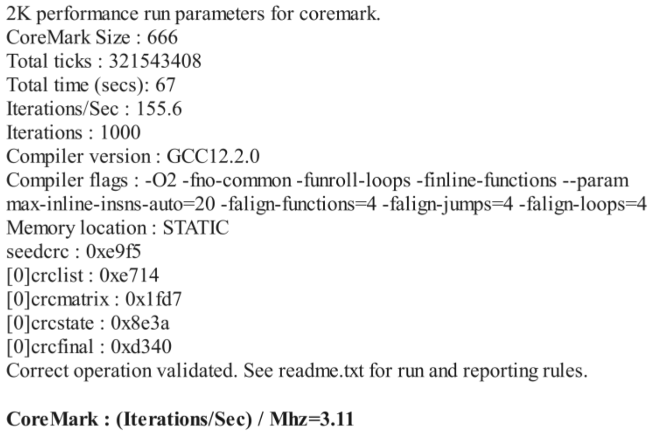

Msgs
...v_tb_vlg_tst/clk_i 1
...tb_vlg_tst/n_rst_i 1
...e_top0/if_id0/pc_i 000002dc
0... 000002b0 000002b4 000002b8 000002bc 000002c0 000002c4 000002c8 000002d4 000002d8 000002dc 000002e0 000002dc
..._top0/if_id0/inst_i 0000006f
00108093 00300e93 01500193 01d09463 00301863 00100d13 00100d93 0000006f 00000000 0000006f
...core_top0/id0/pc_i 000002dc
0... 000002a0 000002b0 000002b4 000002b8 000002bc 000002c0 000002c4 000002c8 000002d4 000002d8 000002dc 000002e0 0...
...re_top0/id0/inst_i 0000006f
0... 00000013 00108093 00300e93 01500193 01d09463 00301863 00000013 00100d13 00100d93 0000006f 00000013 0...
...op0/regfile0/regs... 00000003
00000000 00000001 00000002 00000003
...op0/regfile0/regs... ffffffff
ffffffff
...op0/regfile0/regs... 00000015
00000014 00000015
...op0/regfile0/regs... 00000003
00000003

Fig. 8. Validation of JAL instructions.

B. Performance Test

CoreMark is a straightforward yet sophisticated benchmark designed specifically to evaluate the performance of a processor core. In this paper, the CoreMark program and the NRP processor core were ported to Xilinx's ARTYA7-35T development board using Vivado, and the clock function and serial print function were rewritten. The main frequency of the NRP processor core was set to 50MHz for testing, and the results were transmitted to a PC for display via a serial tool. Fig. 9 presents the serial print results, showing that the NRP processor achieved a final CoreMark score of 3.11 CoreMark/MHz.



```
2K performance run parameters for coremark.
CoreMark Size : 666
Total ticks : 321543408
Total time (secs): 67
Iterations/Sec : 155.6
Iterations : 1000
Compiler version : GCC12.2.0
Compiler flags : -O2 -fno-common -funroll-loops -finline-functions --param
max-inline-insns-auto=20 -falign-functions=4 -falign-jumps=4 -falign-loops=4
Memory location : STATIC
seedcrc : 0xe9f5
[0]crclist : 0xe714
[0]crcmatrix : 0x1fd7
[0]crcstate : 0x8e3a
[0]crcfinal : 0xd340
Correct operation validated. See readme.txt for run and reporting rules.

CoreMark : (Iterations/Sec) / Mhz=3.11
```

Fig. 9. CoreMark scores [20].

C. Experimental Analysis

We implemented various versions of the NRP processor in Verilog HDL and evaluated their performance on Xilinx's ARTYA7-35T development board. Based on the optimization level of the NRP processor, we categorized it into three versions. The version without any optimization design is defined as NRP-Original, the version with optimization design only in the decode stage is defined as NRP-OptID, and the version with simultaneous optimization design in the decode stage and branch predictor is defined as NRP-Final.

Fig. 10 displays the CoreMark scores for each version of the NRP processor. After optimizing the design of the ID stage and the branch predictor, the performance of the NRP processor improved by 11.07%.

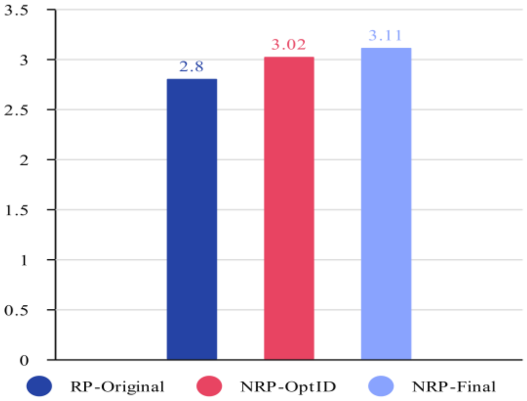


Fig. 10. Performance test results of different versions of NRP.

Fig. 11 presents the CoreMark test results for other open-source processors, showing that the performance of the NRP processor is significantly better than that of other processors [21]-[27].

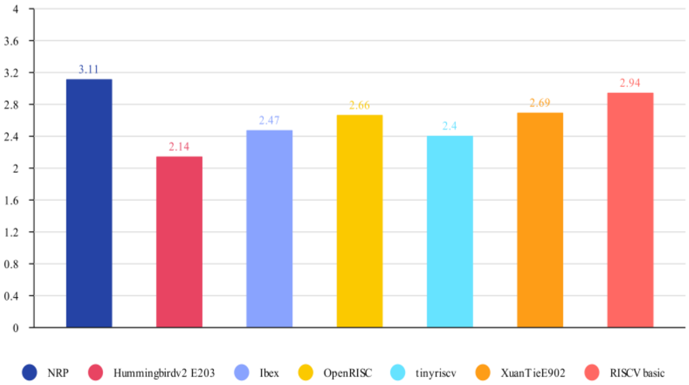


Fig. 11. Performance comparison of different open-source processors.

VI. Conclusion

We have proposed a five-stage pipelined processor based on RISC-V architecture. In this processor, we have employed instruction decoding unit optimization and branch prediction optimization as effective methods to improve operating frequency. We implemented the proposed processor in Verilog using Vivado and conducted tests and evaluations on the processor's performance and hardware resource consumption. The CoreMark test results for the NRP processor after adopting optimization strategies show a score of 3.11 CoreMark/MHz, representing an 11.07% improvement over the non-optimized design.

This research improves the performance of the five-stage pipeline processor based on RISC-V, which can improve the application range of the five-stage pipeline processor and promote the development of the community ecology of RISC-V instruction set architecture. In the future work, we will extend the design of this paper to the five-stage pipeline design of out-of-order execution, and reduce the impact of correlation conflicts on processor performance in out-of-order execution.

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Enhancing Thyroid Cancer Diagnostics Through Hybrid Machine Learning and Metabolomics Approaches

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***Abstract*—Thyroid cancer, a prevalent endocrine malignancy, necessitates advanced diagnostic techniques for accurate and early detection. This study introduces an innovative approach that integrates hybrid Machine Learning (ML) algorithms with metabolomics, offering a novel pathway in thyroid cancer diagnostics. Our methodology employs a range of hybrid ML models, combining the strengths of various algorithms to analyze complex metabolomic data effectively. These models include ensemble methods, neural network-based hybrids, and integrations of unsupervised and supervised learning techniques, tailored to decipher the intricate patterns within metabolic profiles associated with thyroid cancer. The study demonstrates how these hybrid ML algorithms can efficiently process and interpret metabolomic data, leading to enhanced diagnostic accuracy. By leveraging the distinct characteristics of each ML model, our approach not only improves the detection of thyroid cancer but also contributes to a deeper understanding of its metabolic underpinnings. The findings of this study pave the way for more personalized and precise medical interventions in thyroid cancer management, showcasing the potential of hybrid ML models in revolutionizing cancer diagnostics. Our system analyzes thyroid cancer metabolomic data using ensemble methods, neural network-based hybrids, and unsupervised and supervised learning integrations. The research shows hybrid ML models may revolutionize cancer diagnoses by improving accuracy. LSTM+CNN, LSTM+GRU, and CNN+GRU have high accuracy rates, helping us comprehend thyroid cancer's biochemical roots. Hybrid ML models enhance thyroid cancer diagnosis and management, enabling more tailored and accurate medical treatments. The hybrid machine learning models like LSTM+CNN, LSTM+GRU, and CNN+GRU beat CNN, VGG-19, Inception-ResNet-v2, decision support, and random forests (99.45%).**

***Keywords*—Thyroid cancer; hybrid ML models; metabolomics; diagnostic accuracy**

I. Introduction

AI improves diagnosis, treatment, and care. AI's pattern recognition, predictive analysis, and decision-making skills enable computers to analyze complicated medical data with unprecedented precision and scale [1, 2]. This discovery enhances early sickness detection, precise diagnosis, and individualized therapy. AI technologies enhance hospital operations, predict disease outbreaks, and significantly improve patient outcomes. AI is critical to provide equitable access to high-quality treatment across geographic boundaries. As AI advances, it will improve global health outcomes with increasingly complex healthcare applications. However, healthcare AI adoption is hard. User adoption of AI-driven help requires trust. Studying security, risk, and trust on healthcare, AI adoption shows that trust is crucial. Oncology's leading killer affects several organs [3, 4]. Thyroid carcinoma is a prevalent endocrine malignancy worldwide. The sixth most prevalent cancer in women aged 15–49 is thyroid cancer, hence better identification and treatment are needed (see Fig. 1). Thyroid cancer is becoming more common, and machine learning and metabolomics may enhance detection and therapy [5, 6, and 7].

Thyroid cancer has increased in recent decades, with the American Cancer Society expecting 43,800 new cases and 2,230 fatalities in 2022 [8]. Thyroid cancer develops as a nodule at the throat's base when cells proliferate rapidly and escape the immune system. Unregulated cell reproduction spreads rogue cells into surrounding tissues. About 95% of thyroid malignancies are follicular or papillary. Effective management and damage reduction require early discovery and treatment of malignant thyroid nodules. Early thyroid cancer screening detects cancerous nodules. Neck palpation during physical examinations and ultrasonography, which may detect nodules smaller than 1 cm, are the main detection modalities. Ultrasonography helps distinguish benign from malignant nodules by their features [9].

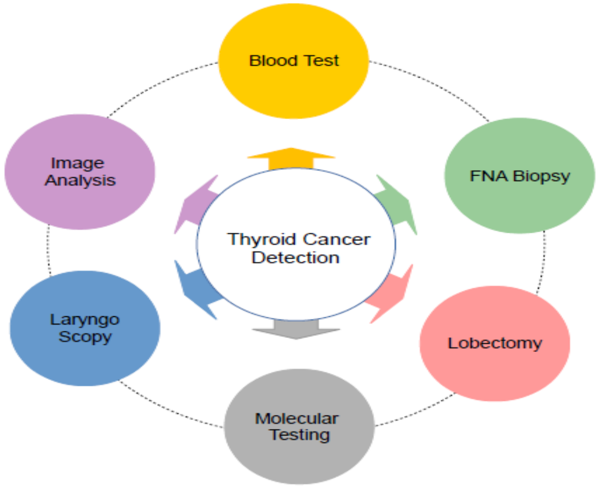

Fig. 1. Various methods for detection of thyroid cancer.

Automated thyroid nodule identification using computer-aided diagnostic (CAD) has evolved in recent years [10]. CAD tools using artificial intelligence analyze ultrasound features more intelligently, accurately, and consistently. This helps decrease needless biopsies. Machine learning and deep learning, key components of AI-based CAD systems, have changed medicine. These approaches use expert knowledge to choose important attributes from predetermined region-of-interest criteria. Margin, form, echogenicity, calcifications, and composition in thyroid ultrasound images have helped build CAD systems. Support vector machines, GoogLeNet, and CNNs have transformed thyroid nodule detection, according to previous studies. Machine learning and AI have greatly improved the use of CAD tools in clinical practice [11].

In thyroid cancer, early and accurate detection may save lives. This cancer survives better with early detection and treatment [12]. Early detection may reduce benign tumor treatment costs and stress. Doctors can enhance patient care with fast and appropriate treatment. Cancer detection employs image processing, deep learning, and AI, notably in medical imaging. Reduce noise in ultrasound images to identify thyroid cancer. Next, segmentation separates cancer-prone regions. Cancerous or benign nodules are determined by these sites. First, gather ultrasound images, then segment them to focus on the affected area. These segments' attributes constitute a predictive model, and a classifier predicts [13]. The neck gland's thyroid carcinoma is treated better with early detection. Healthcare professionals use machine learning algorithms to handle pandemics and natural disasters [14]. These algorithms help physicians identify and treat patients by analyzing enormous medical data. Thyroid CAD systems must be precise to minimize delays or unnecessary treatments. Deep learning-enhanced ultrasonography detects thyroid cancer using complex acoustic features. CAD and AI enhance thyroid cancer diagnosis. They simplify ultrasound-based risk categorization and enhance thyroid nodule identification and assessment. Traditional diagnostic methods like FNAB are 20% incorrect. Machine learning improves insights and judgments using probability and statistics. ML-based classification models using large image datasets are promising for study. Progress is shown by statistical pattern identification and quantification algorithms in thyroid node categorization systems like AmCAD-UT [15].

In this paper, the advent of deep learning models, particularly Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), and their hybrid combinations like LSTM+CNN, LSTM+GRU, and GRU+CNN, presents a transformative approach in thyroid cancer diagnostics. These advanced computational models offer unparalleled precision in analyzing complex medical data, significantly enhancing our ability to detect and diagnose thyroid cancer early and accurately. As we continue to integrate these sophisticated AI methodologies into medical practices, the potential for improving patient outcomes and revolutionizing the field of oncology is immense.

II. Related and Recent Work

AI has substantially improved medical diagnostics, notably tricky thyroid disorders. Improved ultrasound picture interpretation and quicker processing are the main reasons. Ultrasonography, FNA, and thyroid surgery now utilize deep learning (DL) and machine learning (ML) to classify thyroid nodules automatically [16]. Many research have shown AI's potential in cancer detection, where data volume and classification accuracy are critical. Ultrasound, CT, MRI, radioactive iodine, and histopathology diagnosis thyroid cancer. Many research have built AI-based CAD models to detect thyroid abnormalities in ultrasound and histopathological pictures. Xu et al. created a contrast-enhanced thyroid ultrasound diagnostic model using CNN feature extraction and LSTM classification. Zhao et al. offered CNN-extracted characteristics and image texture for ultrasonography thyroid classification [17]. CNNs classify thyroid and breast cancer ultrasound images, whereas U-Net models segment thyroid ultrasounds. Additionally, multi-scale region-based detection networks like Resnet50 and ZFnet are more accurate. Transfer learning reduces overfitting in thyroid nodule classification models employing inception networks, VGG16, and GoogLeNet. Using simple CNN models and spatial and frequency domains, Nguyen et al. categorized the TDID dataset using voting ensemble [18]. In ensemble learning, hunger games search algorithm and D-CRITIC TOPSIS model ranking educated deep vision Transformer and Mixer models. Sun et al. employed the TC-ViT model, a vision transformer with contrast learning, to classify thyroid imaging data by TI-RADS scores [19].

New AI technologies may standardize and enhance uncertain thyroid nodule categorization. Digital thyroid fine needle aspiration biopsy images are employed in these studies. EfficientNetV2-L image classification works in thyroid fine needle aspiration cytology, according to Hirokawa et al [20]. Kezalarian [21] studied AI's role in follicular cancer vs. adenoma, whereas Alabrak et al. proposed a CNN model with good accuracy, sensitivity, specificity, and AUC-score [22].

AI-based thyroid pathology whole slide image analysis utilizing modified QUADAS-2 was evaluated by Girolami et al [23]. Using numerous histopathology pictures, Wang et al. trained VGG-19 and Inception-ResNet-v2 models to diagnose thyroid diseases [24]. Chandio et al. suggested a CNN-based MTC detection decision support system. Hossiny et al. correctly identified thyroid tumors using cascaded CNN and split classification [25]. Do et al.'s thyroid cancer MI Inception-v3 model improved classification accuracy [26]. Bohland et al. found feature-based and deep learning-based thyroid carcinoma classification equivalent [27]. Transformer and Mixer models improve vision, but thyroid feature extraction is uncertain. Vector redundancy may cause feature extraction overfitting. Espadoto et al.'s dimensionality reduction survey was impressive [28]. Meta-heuristic feature selection approaches like moth flame and cuckoo optimization are common for high-dimensional datasets. In data-limited medical disciplines, ensemble techniques using numerous weak learners increase classification model accuracy. The weighted average ensemble technique is intriguing, but weight selection is tricky. FOX optimization, which performs well in traditional benchmarks, holds potential in feature selection and ensemble learning but has not been implemented [14].

TABLE I. COMPARATIVE STUDY ON VARIOUS METHODS FOR DETECTION OF THYROID CANCER

Authors	Method	Accuracy	Key Contributions
Alabrak et al. 2023 [22]	CNN model	78%	Proposed a CNN model to classify thyroid cancer with good accuracy, sensitivity, specificity, and AUC-score.
Wang et al. 2019 [24]	VGG-19 and Inception-ResNet-v2 models	97.34% and 94.42%	Trained models to diagnose thyroid diseases using histopathology images.
Chandio et al. 2020 [39]	CNN-based decision support system	99.00%	Suggested a system for detecting medullary thyroid cancer using CNN.
Hossiny et al. 2021 [25]	Cascaded CNN and split classification techniques	98.74%	Identified thyroid tumors with high accuracy.
Bohland et al. 2021 [27]	Feature-based and deep learning-based models	89.70% (feature-based), 89.10% (deep learning-based)	Comparison of thyroid tumor classification models.
Kouznetsova et al. (2021) [34]	ML model using saliva metabolites	Not Specified	Differentiated between malignant oral lesions and periodontitis.
Cai et al., 2015 [35]	Random forest ML model	86.54%	Classified lung cancer using DNA methylation markers.

The American Thyroid Association endorsed intraoperative frozen sections (FSs) for classical papillary thyroid cancer detection in 2015. However, onsite pathologists may struggle to detect rare cancers and poorly prepared specimens using paraffin sections. PTC is one of the most frequent thyroid cancer, although follicular, medullary, and undifferentiated carcinomas stain poorly. Rare lung and breast cancers are hard to diagnose. Diagnostic discrepancies and CNN model building are difficult due to the lack of pathological imaging data from uncommon cancers [29]. Computational pathology must find rare or intermediate groupings. Deep learning in several fields, including CNNs and RNNs, has led to computer-aided histopathological diagnostic systems. Digital pathology allows histopathological diagnosis using deep learning algorithms. Thanks to CAMELYON16 and the TCGA, patch-based CNNs for whole-slide images (WSIs) have improved cancer histology [30]. CNN methods for breast cancer lymph node metastatic diagnosis are examined. InceptionV3, utilizing CAMELYON16, achieves 98.6% AUC and 87.3% FROC. WSI patch image analysis using Resnet and conditional random fields was also helpful [31]. CNNs are cancer-trained and tested. On TCGA non-small cell lung cancer histopathology pictures, InceptionV3 and pathologists fared similarly. Deep learning model interpretability has improved with new bladder cancer and other cancer screening methods. Positive pathologist diagnostic accuracy comparisons [32].

ML has been used for about two decades to diagnose and track cancer. Cancer diagnosis has relied on decision trees and ANNs since the mid-1980s [33]. Age, health, sickness kind, location, tumor grade, and size affect cancer prognosis. ML predicts nodes and patient severity using this data. Protein markers and microarray data are used in breast and prostate cancer research to identify cancer types, predict risk, and test patients. Diagnostics improve using ML models for CT scans and cancer image projection. ML models to aid doctors in these imaging methods were recognized by the NCI (2022). Metabolomics has been used in cancer research. Research into cancer metabolites has advanced. In bladder cancer (BCa) studies, ML compared metabolite patterns at different stages. Metabolites in healthy and oral cancer patients are linked via these pathways. Using ML, Kouznetsova et al. (2021) distinguished malignant from periodontitis oral lesions using saliva metabolites [34]. Genomic data was used by ML-based classifiers to construct a lung cancer DNA methylation indicator panel. A random forest ML model diagnosed lung cancer with 86.54% accuracy by Cai et al., 2015 [35]. These results show ML's growing role in cancer diagnostic accuracy and efficiency, paving the way for future research (see Table I).

III. METHODOLOGY

A. Long Short-Term Memory (LSTM)

The Recurrent Neural Network (RNN) LSTM may learn long-term data sequence relationships. This is valuable in medical diagnostics, as patient data covers extended periods and includes important sequential patterns. The input, forget, and output gates make up LSTM. These gates regulate cell state information flow, enabling the network to remember or forget [36, 37]. This approach uses LSTMs to evaluate and understand complicated metabolic data and other temporal information. Metabolic marker alterations, thyroid symptom progression, and diagnostic data integration are included. The input, forget, and output gates of LSTM control information flow, making it effective. These gates determine what data to keep or discard as the data sequence proceeds, allowing the model to keep important data and forget non-essential data [40].

Equations for LSTM:

Forget Gate selects cell state data to discard. It examines the previous state (h_{t-1}). The program produces a value between 0 and 1 for each cell state (C_{t-1}) and current input (x_t).

$$f_t = \sigma(W_f[h_{t-1}, x_t] + d_f)$$

Input Gate: A sigmoid layer chooses values to update while a tanh layer creates a vector of candidates.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i)$$
$$C'_t = \tanh(W_C[h_{t-1}, x_t] + b_C)$$

The previous cell state is updated to the new one.

$$C_t = f_t * C_{t-1} + i_t * C'_t$$

Output Gate: It selects the next hidden state representing prior inputs.

$$O_t = \sigma(W_o.[h_{t-1}, x_t] + b_o)$$
$$h_t = O_t * \tanh(C_t)$$

LSTM can analyze consecutive metabolic profiles and historical patient data to capture temporal relationships needed for thyroid cancer diagnosis and prognosis. Combining LSTM with additional machine learning methods like CNNs for image analysis improves thyroid cancer diagnosis.

B. Gated Recurrent Units (GRU)

GRUs are Recurrent Neural Networks (RNNs) intended to analyze data sequences. It is fewer gates and are simpler and more efficient in certain cases. Medical diagnostics use GRUs to capture temporal connections in sequential data. GRUs might assess time-dependent changes in metabolites, hormone levels, and other biochemical indicators of thyroid disorders to diagnose thyroid cancer [38].

Integrating the “forget and input” gates into one GRU simplifies RNNs "update gate." They also use a "reset gate." These two gates in GRUs control the information flow within the unit, which is essential for maintaining relevant information over different time steps.

Equations for GRU:

Update Gate: Determines how much previous knowledge to pass on.

$$z_t = \sigma(W_z[h_{t-1}, x_t])$$

Reset Gate: Decides how much of the previous knowledge to forget.

$$r_t = \sigma(W_r[h_{t-1}, x_t])$$

Current Memory Content: **Creates** the candidate which will be used to update the cell state.

$$h'_t = \tanh(W.[r_t.h_{t-1}, x_t])$$

Final Memory at Current Time Step: **Combines** the old state with the new candidate state

$$h_t = (1 - z_t) * h_{t-1} + z_t * h'_t$$

GRUs' basic design lets them store key data from prior data points and reject irrelevant data, improving their sequential data prediction abilities. Instead of update and reset gates, GRUs use a simpler gating method. The gates regulate how much previous knowledge to pass on to the future, improving sequential data learning. For a complete examination, we will use GRUs and other machine learning methods like CNNs.

C. Convolutional Neural Networks (CNN)

CNNs are powerful deep neural networks for visual analysis. They excel in automatically detecting and learning spatial hierarchies of characteristics from pictures, which is essential for thyroid cancer detection in medical imaging [39]. Convolutional, pooling, and fully linked layers make up a CNN. The output of a convolution process is sent to the next layer. The network builds a learnt feature hierarchy this way.

Equations for CNN:

Convolution Operation:

$$F_{ij} = \sum_m \sum_n I_{(i+m)(j+n)} K_{mn}$$

where, F_{ij} is the output feature map, I represents the input image, and K is the kernel or filter applied to the image.

Activation Function (ReLU): $f(x) = \max(0, x)$ used to provide the model non-linearity to learn more complicated patterns.

Pooling Operation (Max Pooling): $P_{ij} = max(I_{(i:i+p)(j:j+p)})$ where P_{ij} is the output after pooling, and I the input feature map, and p the pooling window size. As in ordinary neural networks, neurons in the final layers are completely coupled to all activations in the preceding layer. This part is typically used to classify features learned by the CNN into different categories.

This approach analyzes thyroid ultrasound pictures using CNNs. Their capacity to extract and learn key elements from these photos is critical for thyroid cancer detection. CNN and LSTM or GRU will evaluate non-imaging data together. CNNs extract features from pictures, whereas LSTM/GRU models analyze consecutive patient histories and metabolic profiles. This integrated strategy improves thyroid cancer diagnosis and monitoring accuracy and efficiency.

D. Hybrid model LSTM+CNN

The hybrid LSTM-CNN model is crucial. LSTM and CNN models work well together to analyze complicated sequence and picture datasets. This hybrid technique combines LSTM sequential data processing with CNN spatial feature extraction. It is suitable for diagnostic situations that need both time-series data (like metabolic profiles) and imaging data (like ultrasound pictures).

Equations for LSTM+CNN:

CNN Layer:

$$F_{ij} = \sum_m \sum_n I_{(i+m)(j+n)} K_{mn}$$

where, F_{ij} is the output feature map, I represents the input image, and K is the kernel or filter applied to the image. This equation represents the convolution operation in the CNN layer, crucial for extracting spatial features from images.

LSTM Layer:

$$h_t = O_t * \tanh(C_t)$$

where, h_t is the output of the LSTM cell at time t, O_t is the output gate, and C_t is the cell state. This LSTM equation is responsible for processing sequential data, maintaining important information over time.

Thyroid ultrasound pictures are processed by CNN to extract essential details. The LSTM component receives extracted characteristics. This section of the model handles time-series data like metabolic marker changes and symptom development. The temporal interpretation of these traits by the LSTM layers provides crucial information regarding thyroid cancer growth and status. Combining ultrasound pictures with patient history and metabolic data makes this hybrid model useful for thyroid cancer diagnosis. It provides a complete knowledge of the condition, which may improve diagnosis and therapy. LSTM and CNN work together in this hybrid model to record and evaluate spatial and temporal patterns.

E. Hybrid model LSTM+GRU

To handle and comprehend complicated sequential data, a hybrid model uses LSTM networks and GRUs. This hybrid model combines LSTM and GRU capabilities. GRUs change network information flow, whereas LSTMs remember information over extended durations. This combination improves the model's sequential data processing, which is useful for medical diagnostics time-series data analysis.

Equations for LSTM+GRU:

LSTM Layer

$$h_t = O_t * \tanh(C_t)$$

where, h_t is the LSTM cell output at time t, O_t is the output gate, and Ct is the cell state. This equation is essential for the LSTM to retain important information over time..

GRU layer:

$$h_t = (1 - z_t) * h_{t-1} + z_t * h'_t$$

where, h_t is the output at time t, z_t is the update gate, h'_t is the candidate activation, and h_{t-1} is the previous output. This equation helps the GRU balance old and new data. The model's LSTM component captures patient data's long-term dependencies and correlations by processing sequential data. GRU processes the LSTM layer output. It changes information flow to concentrate on the most important parts for the diagnostic job. The hybrid model is ideal for analyzing complicated medical data over time because it uses LSTM's capacity to recall information over longer sequences and GRU's efficiency in updating the hidden state. This LSTM+GRU hybrid model is ideal for assessing sequential medical data like metabolic alterations and thyroid disease development. For accurate thyroid cancer detection and progression, the model incorporates long-term and short-term data dependencies using LSTM and GRU. A more detailed examination using the hybrid method may lead to more accurate diagnosis and targeted therapy.

F. Hybrid model CNN+GRU

A CNN-GRU hybrid model is used. This combo processes imaging and sequence data to diagnose thyroid carcinoma comprehensively. This model combines CNN spatial feature extraction with GRU sequential data processing. CNNs thrive in imaging data analysis and interpretation, while GRUs excel at time-series data analysis, making this hybrid model ideal for medical applications that need both.

Equations for CNN+GRU:

CNN Layer:

$$F_{ij} = \sum_m \sum_n I_{(i+m)(j+n)} K_{mn}$$

where, F_{ij} is the output feature map, I represents the input image, and K is the kernel or filter applied to the image. This equation represents the convolution operation in the CNN layer, crucial for extracting spatial features from images.

GRU layer:

$$h_t = (1 - z_t) * h_{t-1} + z_t * h'_t$$

where, h_t is the output at time t, z_t is the update gate, h'_t is the candidate activation, and h_{t-1} is the previous output. This GRU equation manages the flow of information, balancing the retention of previous state information with new inputs Thyroid ultrasound pictures are processed by the CNN component to extract important spatial characteristics. The GRU component receives extracted characteristics. The GRU analyzes time-series data like metabolic marker changes and patient symptoms. CNN and GRU help the model gain insights from static pictures and dynamic sequential data, improving diagnostics. For various data analysis in thyroid cancer diagnosis, the CNN+GRU hybrid model is powerful. CNNs analyze ultrasound pictures to find thyroid cancer indicators, whereas GRUs evaluate patient-specific temporal data for a more accurate diagnosis. This method should enhance thyroid cancer identification and therapy.

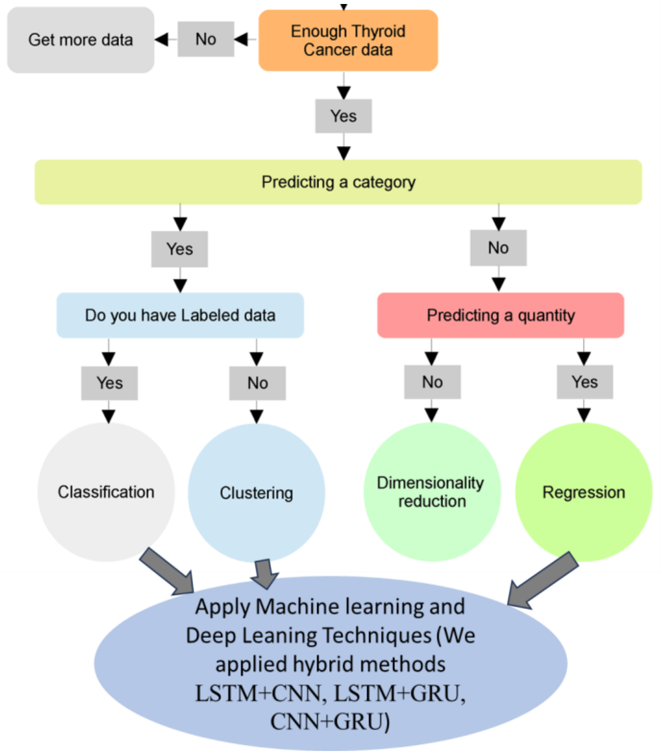

Fig. 2. Implementation process for predicting thyroid cancer.

This study reviews AI-based thyroid gland (TG) cancer diagnostic methods. Fig. 2 proposes categorizing AI-based thyroid cancer diagnostic methods. Considering tumor size, location, and patient age, and health, thyroid carcinoma categorization is crucial for appropriate treatment techniques. AI and machine learning have improved thyroid cancer classification automation and accuracy. CNNs and the U-Net architecture are increasingly employed for thyroid cancer segmentation because to their capacity to learn and generalize from big datasets. Applied Machine Learning and Deep Learning Techniques, such as LSTM+CNN, LSTM+GRU, and CNN+GRU, improve thyroid cancer detection.

IV. DATASET DETAILS

The Thyroid Disease dataset, graciously contributed on December 31, 1986, includes 10 Garavan Institute datasets. This multivariate, domain-theory dataset is for categorization in health and medicine. This dataset contains category and actual characteristics with various information. A unique dataset with 7200 occurrences and five characteristics is available for investigation. The Garavan Institute in Sydney, Australia, created six databases with 2800 training and 972 test examples each. These databases have several missing data points and 29 Boolean or continuously-valued features. In addition to the Sydney databases, Ross Quinlan's hypothyroid, data and sick-euthyroid, data present corruption concerns. Despite this, their format matches other databases. Another thyroid database by Stefan Aeberhard contains three classes, 215 instances, and five attributes without missing values (see Fig. 3).

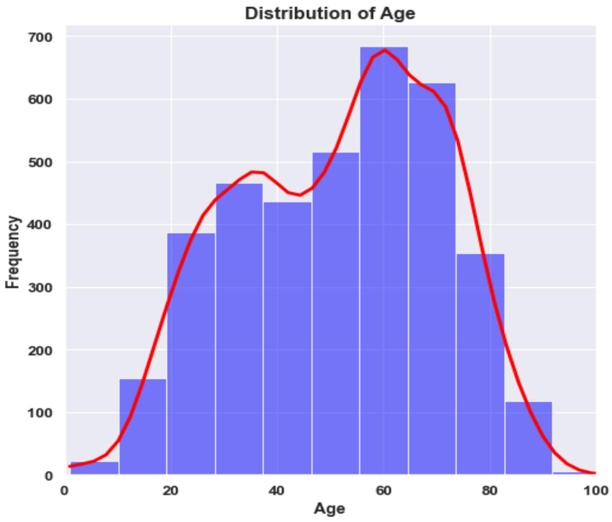

Fig. 3. Distribution of age for dataset.

The dataset contains several factors that may be used for thyroid analysis. The dataset's 'age' attribute is a significant demographic component. The variable'sex' shows gender distribution, revealing thyroid-related parameter gender differences. 'On thyroxine', 'query on thyroxine', 'on antithyroid medication','sick', 'pregnant', 'thyroid surgery', 'I131 therapy', 'query hypothyroid', 'query hyperthyroid', 'lithium', 'goitre', 'tumor', 'hypopituitary', and 'psych' are important binary variables These binary indicators reveal the presence or absence of certain illnesses or treatments, providing a complete health picture. The collection comprises thyroid hormone readings and levels. Variables like 'TSH measured', 'TSH', 'T3 measured', 'T3', 'TT4 measured', 'TT4', 'T4U measured', 'T4U', 'FTI measured', 'FTI' quantify thyroid-stimulating hormone (TSH), triiodothyronine (T3), thyroxine (TT4), and other These measures are essential for thyroid function testing. The dataset also includes 'TBG measured' and 'TBG' thyroxine-binding globulin readings. These measures add complexity to the dataset, enabling more detailed thyroid function evaluations (see Fig. 4).

The variable' referral source' indicates the participant's referral source, giving context for the data. Finally, the target variable 'binaryClass' indicates a thyroid-related condition's existence or absence. This prospective study monitored 383 patients for at least 10 years over 15 years. We aimed to predict recurrence in this patient cohort. The 13 clinicopathologic variables were extensively examined to predict recurrence. Patients in the study had a wide demographic, with a mean age of 40.87 ± 15.13 years. The population was 81% female. Gender distribution may alter sickness patterns and consequences, contextualizing the study's findings. A decade and 15 years of study revealed recurrence's temporal dynamics. Capturing complicated health histories with several clinicopathologic parameters created a sophisticated recurrence prediction model.

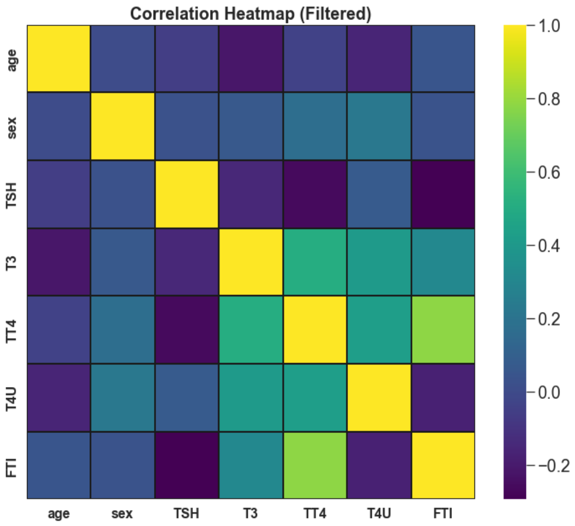

Fig. 4. Correlation matrix for dataset.

With its lengthy observation period and detailed clinicopathologic examination, this rigorous cohort study can evaluate and predict recurrence in a diverse patient population. Age and gender increase the dataset and enlighten sickness recurrence studies. The dataset employed in this research work encompasses a variety of clinical and demographic features crucial for evaluating the likelihood of thyroid cancer diagnosis. These features include mean radius, texture, perimeter, area, and smoothness, providing insights into the physical characteristics, structural properties, and extent of thyroid growths. The dataset's target variable, diagnosis, categorizes individuals into "benign" and "malignant" classes, serving as the label for machine learning predictions. This comprehensive dataset enables a thorough analysis for predicting thyroid cancer diagnoses based on diverse patient attributes.

V. RESULTS AND DISCUSSIONS

Thyroid cancer is a worldwide health issue that requires novel diagnostic methods. We build a powerful hybrid model using machine learning and metabolomics to handle this challenge. These methods attempt to improve thyroid cancer diagnostic accuracy and reliability, improving patient outcomes. After analyzing the complete dataset, specific indicators predicted thyroid cancer recurrence.

TABLE II. ANALYSIS OF DIFFERENT ML METHODS WITH FIVE FOLDS

Method	Fold	Accuracy	Precision	Recall	F1 Score
CNN	1	97.35	86.78	87.67	79.91
	2	97.68	87.67	88.36	80.63
	3	97.11	86.12	87.23	79.34
	4	98.24	88.67	89.45	81.79
	5	98.57	89.56	90.67	83.12
LSTM	1	97.89	87.78	88.56	80.67
	2	98.36	88.89	89.89	82.34
	3	98.25	88.12	89.23	81.56
	4	99.25	90.67	91.78	84.23
	5	98.79	89.34	90.45	83.45
Bi-LSTM	1	98.68	89.89	90.78	84.01
	2	98.9	90.45	91.34	84.67
	3	98.57	89.23	90.34	83.01
	4	99.24	91.56	92.45	85.45
	5	98.99	90.78	91.56	84.12
GRU	1	98.21	88.56	89.67	82.01
	2	98.38	89.23	90.45	83.23
	3	97.89	88.45	89.12	82.34
	4	98.68	89.89	90.78	84.12
	5	98.45	89.56	90.34	83.67
LSTM+CNN	1	99.23	92.78	93.45	87.12
	2	99.45	93.45	94.34	88.56
	3	98.89	92.34	93.56	86.89
	4	99.12	93.56	94.23	88.67
	5	99.1	92.78	93.89	87.23
LSTM+GRU	1	99	91.89	92.78	86.12
	2	99.12	92.34	93.34	86.45
	3	98.79	91.23	92.12	85.12
	4	99.23	92.78	93.78	87.78
	5	98.9	91.89	92.78	86.45
CNN+GRU	1	98.12	89.23	90.01	83.12
	2	98.46	89.89	90.78	84.01
	3	97.89	88.45	89.23	82.56
	4	98.68	90.12	91.01	83.78
	5	98.34	89.23	90.12	82.89

We observe that structurally incomplete treatment response (score = 0.843), gender (0.014), low-risk category (0.054), age (0.072), Hurthel cell pathology (0.013), and outstanding treatment response (0.004) were significant predictors. Since there were no node or partitioning depth limits, decision tree models could dynamically alter and capture complex patterns. Our study's accuracy and F1 score values for various approaches at different folds provide exciting new information about the hybrid models' performance. Famous models include the Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Gated Recurrent Unit (GRU), and CNN+GRU, LSTM+CNN, and LSTM+GRU.

The discussion discusses our findings and each hybrid model's merits and weaknesses. Metabolomics data and machine learning methods help us grasp thyroid cancer's molecular landscape. Given the variability of thyroid cancer patients, the observed changes in accuracy and F1 score among folds suggest a nuanced approach. We also found that our hybrid models can capture complicated data linkages better than individual models. Metabolomics data and machine learning algorithms give a comprehensive view of thyroid cancer, possibly revealing novel biomarkers and diagnostic methods. Our results may be translated into clinical settings for more accurate and individualized thyroid cancer diagnosis.

In Table II, the comprehensive results, detailed in the table below, provide a nuanced understanding of each method's accuracy, precision, recall, and F1 score across different folds. The Hybrid LSTM+CNN Model performed well across folds. The model has consistent and strong prediction skills with an accuracy of 97.35% to 98.57%, precision of 86.78% to 89.56%, recall of 87.67% to 90.67%, and F1 Score of 79.91% to 83.12%. It may improve thyroid cancer diagnosis by merging LSTM and CNN architectures. The Hybrid LSTM+GRU Model also performed well in thyroid cancer diagnoses. The model had accuracy scores of 97.89% to 99%, precision of 87.78% to 92.34%, recall of 88.56% to 93.78%, and F1 Score of 80.67% to 87.78% across folds. The model's promising performance shows the benefits of merging LSTM and GRU architectures. In addition, the CNN+GRU Model consistently predicted thyroid cancer in the study. The model is predictively reliable with accuracy values of 97.89% to 98.68%, precision of 88.45% to 90.12%, recall of 89.23% to 91.01%, and F1 Score of 82.56% to 83.78%. CNN and GRU architectures help the model handle thyroid cancer diagnostic complexity. The Hybrid LSTM+CNN, Hybrid LSTM+GRU, and CNN+GRU Models, under the study subject, have promising predictive skills and integrate multiple machine learning architectures to improve thyroid cancer diagnosis. These results aid thyroid cancer diagnostic accuracy efforts.

The Fig. 5 shows accuracy trends throughout folds for the study's machine learning approaches. CNN, LSTM, Bi-LSTM, GRU, LSTM+CNN, LSTM+GRU, and CNN+GRU are illustrated with unique lines to compare performance. Folds (1–5) on the x-axis represent the model's assessment across varied datasets. On the y-axis, accuracy percentages demonstrate each method's predictive power. As compared to individual architectures, the Hybrid LSTM+CNN and GRU models are consistently more accurate. Although significantly varied among folds, the CNN+GRU model has comparable accuracy. Fig. 5 shows that hybrid machine learning methods combined with metabolomics data may improve thyroid cancer diagnosis. The figure's intricate patterns and trends aid thyroid cancer detection technique development.

In the pursuit of advancing thyroid cancer diagnostics, our research employs a hybrid approach, integrating machine learning methodologies with metabolomics techniques. Fig. 6 illustrates the F1 score across different folds for various methods employed in our study, encompassing Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Gated Recurrent Unit (GRU), as well as hybrid models such as LSTM+CNN, LSTM+GRU, and CNN+GRU. Each method is represented with distinct markers and lines, showcasing their performance variability across different folds. The F1 score trends show how well these hybrid machine learning models improve thyroid cancer diagnosis.

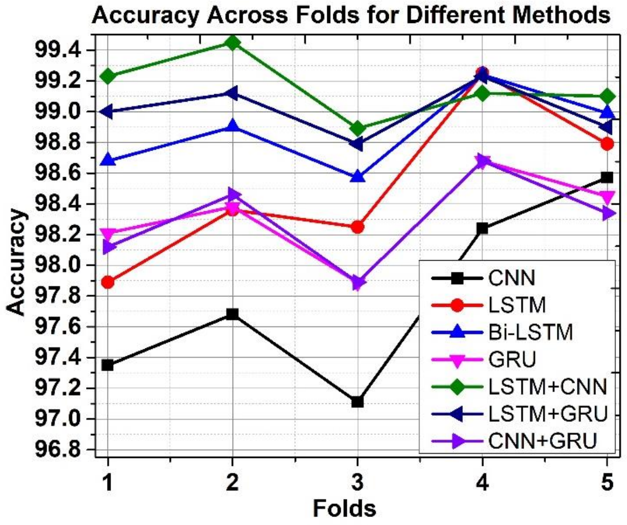

Fig. 5. Comparative analysis of accuracy with various ML methods and hybrid ML algorithms.

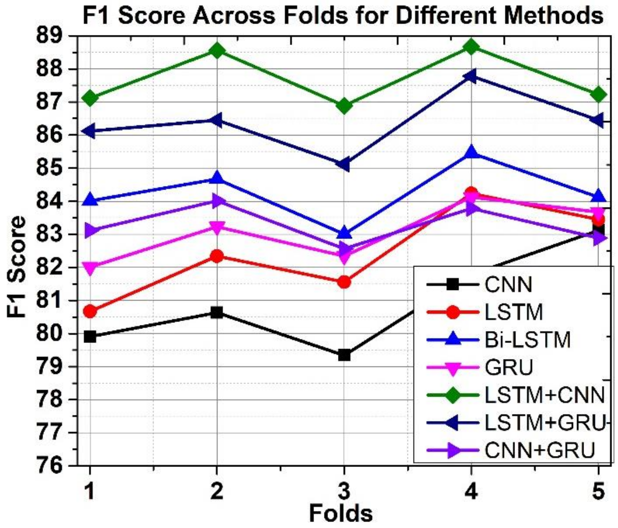

Fig. 6. Comparative analysis of F1 score with various ML methods and hybrid ML algorithms.

Our research compared hybrid machine learning models coupled with metabolomics data to improve thyroid cancer diagnosis. The table shows each method's accuracy, precision, recall, and F1 score across folds. The Convolutional Neural Network (CNN) reliably identified thyroid cancer patterns with 98.57% accuracy. LSTM+CNN and LSTM+GRU hybrid models outperformed standalone models, demonstrating the benefits of joining neural network architectures. Nuanced analysis showed surprising dynamics, with Bi-LSTM balancing accuracy and recall and LSTM+CNN excelling in F1 score. GRU models regularly outperformed 98%, demonstrating the synergy between recurrent neural networks and metabolomics data. LSTM+GRU was a standout hybrid model, outperforming across criteria. Finally, this comparison study helps physicians and researchers use machine learning and metabolomics to diagnose thyroid cancer more accurately.

A. Comparative Study with our Proposed Methods

Comparing hybrid machine learning and metabolomics approaches to thyroid cancer diagnosis examines the performance of different authors' methods. Alabrak et al. [22] used a CNN model and achieved 78% accuracy, demonstrating convolutional neural networks' potential. Wang et al. [24] found 97.34% and 94.42% accuracy in VGG-19 and Inception-ResNet-v2 models, demonstrating the usefulness of sophisticated neural network architectures (see Table III).

TABLE III. COMPARE DIFFERENT RECENT ML METHODS WITH OUR PROPOSED METHODS

Authors	Method	Accuracy
Alabrak et al. 2023 [22]	CNN model	78%
Wang et al. 2019 [24]	VGG-19 and Inception-ResNet-v2 models	97.34% and 94.42%
Chandio et al. 2020 [39]	CNN-based decision support system	99.00%
Hossiny et al. 2021 [25]	Cascaded CNN and split classification techniques	98.74%
Cai et al., 2015 [35]	Random forest ML	86.54%
Proposed model in this paper	Hydrid ML methods (LSTM+CNN, LSTM+GRU, CNN+GRU)	99.1%, 99.12% and 99.45%

Chandio et al. [39] developed a CNN-based decision support system with 99.00% accuracy for thyroid cancer diagnosis. Hossiny et al. [25] achieved 98.74% accuracy using cascaded CNN and split classification. Ensemble learning approaches are versatile, as Cai et al. [35] used a random forest machine learning model to achieve 86.54% accuracy. The hybrid machine learning techniques (LSTM+CNN, LSTM+GRU, CNN+GRU) in our study outperform these models with 99.45% accuracy. This shows that hybrid models, which include LSTM, CNN, and GRU, are better for thyroid cancer diagnosis. The suggested thyroid cancer diagnostic model outperforms individual models and state-of-the-art techniques, indicating clinical applicability and additional study.

VI. CONCLUSIONS AND FUTURE DIRECTIONS

We demonstrated that hybrid machine learning models like LSTM+CNN, LSTM+GRU, and CNN+GRU work. Hybrid models beat CNN, VGG-19, Inception-ResNet-v2, decision support, and random forests (99.45%). According to studies, metabolomics data and advanced machine learning enhance thyroid cancer detection. The hybrid models' high performance exhibits LSTM, CNN, and GRU synergies. These models may enhance thyroid cancer diagnosis and treatment, making them more effective and efficient. Future research should broaden the dataset to ensure model generalizability across patient categories. Exploring hybrid models' interpretability and discovering key qualities that allow correct diagnosis will enhance current methodologies' clinical applicability. Real-world clinical data and healthcare facility validation may further validate the provided models. Scalability and computational efficiency must be evaluated for clinical application of hybrid models. Metabolomics and machine learning should be used to improve thyroid cancer diagnosis models. The combination machine learning-metabolomics research improves thyroid cancer detection. The promising findings might revolutionize the field, boosting patient diagnosis and efficiency.

Future thyroid cancer detection utilizing hybrid machine learning and metabolomics covers several important research topics. First, healthcare organizations must cooperate to gather more and diverse datasets. This cooperation makes models generalizable across demographic groupings and therapeutically useful. Interpretability is crucial for healthcare machine learning model adoption. Further research should enhance hybrid model interpretability to highlight diagnostic patterns. Interpretability helps healthcare practitioners detect thyroid cancer biomarkers and gain confidence. For clinical usage, hybrid models must be scalable and computationally efficient. These models should be optimized for healthcare settings with varying computational resources. Adding the models to healthcare operations may boost acceptability. Metabolomics and machine learning models must evolve to stay ahead. Future research should create methods to benefit hybrid models using metabolomics and machine learning. Multimodal data integration research, encompassing omics and clinical data, is promising. Different data sources may help us comprehend thyroid cancer and build more precise and personalized diagnostic approaches.

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Precision Insulin Delivery: Predictive Modelling for Bolus Insulin Injection in Real-Time

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***Abstract*—Insulin is recommended for patients with Diabetes Mellitus (DM). It is challenging for doctors to prescribe accurate bolus insulin before every meal due to real-time factors such as the size of the meal, skipping a previous meal, and physical activity, which can risk the patient towards hyperglycemia or hypoglycemia. Previous studies executed insulin predictions where the methods did not consider the cases of controlled glucose levels, type of insulin prescribed, time of insulin-induced, and data detersion that can alter the predictions. To address these problems, our work has proposed an insulin predictive model from the integration of Internet of Things (IoT) devices, i.e., Continuous glucose monitoring (CGM) sensor and insulin pumps with rapid-acting insulin type where the insulin dosage with corresponding Current Blood Glucose levels (CBG) and improved Next Blood Glucose levels (NBG) are chosen. The dataset is subjected to data detersion where pre-processing, Exploratory Data Analysis (EDA), and Feature Selection is performed. Machine Learning (ML) models are applied on curated dataset where Decision Tree (DT)-Bagging algorithm, performed the best with a Mean Absolute Error (MAE) of 1.54 and a Mean Square Error (MSE) of 4.15. Performance metrics of the current study imply its suitability in medical applications for accurate prediction of real-time insulin dosage.**

Keywords*—Continuous glucose monitoring; bolus insulin prediction; data curation; data detersion; diabetes mellitus; exploratory data analysis; feature selection; machine learning; pre-processing

I. Introduction

DM is an abnormality where irregular blood glucose levels arise due to the inadequacy of insulin secretion from the pancreas, insulin action in the body, or both [1]. Prediction of insulin is important for making informed decisions to maintain blood glucose levels [2].

A. Background

Previous methods of predicting insulin dosage based on invasive blood glucose collection methods have not considered the type of insulin which varies for every person that can alter the readings [3-4]. Other challenges are fluctuating glucose levels with respect to lifestyle factors such as skipping the previous meal, meal size, uncontrolled food habits, or physical activity. Prescribed insulin dosage may lead to overdosage and underdosage in these cases. Therefore, there is a need of a prediction model for insulin dosage in real-time which can be achieved from IoT devices by acquiring real-time blood glucose from CGM sensor and an insulin pump data to deliver accurate insulin dosages.

A study implemented a Gradient-boosting classifier to predict diabetes and linear regression for predicting insulin dosage from the Pima diabetes dataset and University of California (UCI) insulin dataset. An accuracy of 100% with the Gradient-boosting classifier and 78% with linear regression is achieved [5]. Deep reinforcement learning is implemented for bolus insulin advisors. It is observed that Time in range (TIR) increased for volunteers with bolus insulin advisor from TIR=74.1%±8.4% to 80.9% ± 6.9%, 54.9% ±12.4% to 61.6 ±14.1 [6]. A study discussed predicting insulin levels from 36 months of patient data by implementing Recurrent Neural Network (RNN)-Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN) with an accuracy of 90% [7]. In a similar study of obtaining high MAE on predicting insulin dosage based on predicted glucose levels, Support Vector Regression (SVR) provides MAE of 28mg/dL on CBG, 21mg/dL on average daily glucose levels, and 3.8mg/dL on insulin required in next 24hrs. The study concludes that predicting accuracy is hard because glucose and insulin are highly erratic [8]. A study attempted to predict the initial inpatient Total Daily Dose (TDD). Ensemble learning model, i.e., Ridge regularization, Lasso regression, Random Forest, Gradient boosted DT is implemented where an Area Under Receiver Operating Curve (AUROC) of 0.85 and Area Under Precision-Recall Curve (AUPRC) of 0.66 is achieved [9]. Another study proposed glucose prediction with an accuracy of 98.7% and insulin dosage delivery prediction by employing an ANN. MSE calculated for ANN is 5.79. Feature Selection is carried out to identify the best features for insulin prediction. Data is set to zero when the patient takes no insulin during data processing. This may result in input data variation due to incorrect data patterns [10]. A dataset containing full CBG and insulin-prescribed information is vital for predicting insulin dosage. Other essential parameters, such as carb ratio, Body Mass Index (BMI), and correction factor, must be considered for predicting insulin dosage. In a similar study of initial insulin estimation during hospital admission, an ensemble algorithm with regression, Random Forest (RF), and gradient boosting is applied to classify patients who require more than six units of insulin and TDD. Receiver operating characteristic curve (ROCC) of 0.84 with 95% confidence interval (CI), Area under the curve (AUC) of 0.65 with a 95% CI, and MAE with 12 units of insulin is achieved [11]. MAE obtained is too high for insulin dosage prediction. In a study of gestational diabetes for predicting insulin levels, the Oral Glucose Tolerance Test (OGTT) was considered an independent predictor. Area Under the Curve (AUC) for the prediction of insulin treatment was found to be 0.77[12]. The algorithm can predict insulin and glucose levels by considering other parameters such as BMI, PBG, NBG, and CBG. Weight, fasting blood glucose, and gender are fed into an ANN algorithm for predicting insulin dosage, where an average accuracy of 96.5% and an average prediction error of 4% are achieved [13]. A neural network (NN) based bolus insulin prediction is attempted in a study from CGM. The NN is trained to learn Standard Formula (SF) parameters by examining the Blood Glucose Risk Index (BGRI). The parameters chosen are the Optimal bolus insulin calculator (SF-OPT), found to be 0.40, and the Neural Network Correction factor (SF-NNC), 0.37. Optimal-Neural network corrector (OPT-NNC), i.e.,0.30, Scheiner -Neural network corrector (SC-NNC), i.e., 0.23, Pettus and Edelman (PE-NNC) which is found to be 0.20[14].

The research gaps identified from the above literature are as follows:

1) The existing methods have predicted insulin by considering blood glucose values and their prescribed insulin dosage. The methods haven't focused on evaluating the cases of improved blood glucose levels w.r.t the prescribed insulin dosage. Therefore, the prediction may not be accurate in real-time.

2) Existing literature hasn't focused on the data detersion process [5-14]. Data detersion is vital for fixing ambiguities, errors, and any irrelevant data that may contribute to weakening the model. It is required for generating reliable visualizations and accurate models.

3) Various types of insulin are suggested for patients such as short-acting, ultra short-acting, intermediatory and long-acting insulin with different onset or peak times. The existing methods haven't focused on the type of insulin for predicting insulin dosage. As every type of insulin varies, the predictions are inaccurate and prone to hyperglycemia or hypoglycemia in real-time.

4) Meal intake is a potential discrepancy that influences the prescribed insulin dosage. Existing methods haven't focused on considering meal intake before the prescribed insulin regimen for accurate prediction of insulin dosage.

There is a need to create a multidisciplinary approach for predicting bolus insulin dosage by considering the parameters, i.e., insulin type, meal influence, CBG, improved NBG, and the corresponding insulin dosage. This attempt trains the model accurately by considering the suitable insulin dosages w.r.t the CBG. Data detersion is required to ensure that the reliability and accuracy is achieved by removing the outliers, inconsistencies to avoid skewed results by improving the quality of data for insightful information. This is our rationale to implement an advanced method of insulin prediction based on CBG and NBG [15] and data detersion methods. To our knowledge, this work is the first attempt from the existing literature to apply various methods of data detersion and prediction of bolus insulin from CBG and NBG levels, i.e., blood glucose recorded after half an hour of inducing bolus insulin. The outcome of the prediction is applicable in making informed clinical decisions, treatment titrations, changes in lifestyle habits, evidence-based dosage recommendations based on the patient's historical data, treatment outcomes, and the patient's response to the drug and clinical trials of insulin drug dosage. The novel contribution of the work is as follows:

1) The novelty of the proposed work is to create a prediction model from CBG and improved NBG for predicting accurate bolus insulin dosage.

2) Among all ML models, a striking improvement with 39.7% (from 3.12 to 1.88) in MAE and 72.7% (from 17.52 to 4.78) in MSE with ANN is achieved after applying Feature Selection.

3) After applying data detersion, the datasets improved the performance with 47.4% (from 3.12 to 1.64) in MAE and 76.2% (from 17.52 to 4.16) in MSE with the ANN model.

4) Bagging and boosting enhanced the performance of the dataset when compared with non-bagging and non-boosting models. An improvement of 35.5% in MAE (from 2.39 to 1.54) and 78.1% MSE (from 18.96 to 4.15) with DT-Bagging is achieved. Similarly,10% in MAE (from 2.39 to 2.13) and 56.6% MSE (from 18.96 to 8.22) with DT-Boosting is achieved.

The proposed work is organized as follows: Section II presents Material and Methods where data collection and cohort, data preparation, and data detersion are carried out. Data pre-processing, EDA, and feature selection are employed in data detersion method. Section III presents the Results and Discussion section, where bolus insulin prediction, predictive analysis, and validation of the DT-Bagging model are executed. The paper ends with Section IV, an exposition on the conclusion.

II. Materials and Methods

This section presents the experimental workflow, starting with data collection, as illustrated in Fig. 1. In data preparation, essential features and a dataset are extracted from the CGM sensor. The procedures and processes for data detersion i.e., data pre-processing, EDA, feature selection, are executed.ML algorithms are applied on the data detersion applied datasets for validation.

A. Data Collection and Cohort

Ethical clearance was obtained from the SRM Medical College Hospital and Research Centre, Kattankulathur-603203, Tamil Nadu, India (Ethical clearance number:-8274/IEC/2022). A publicly available 'closed-loop control to range system' public dataset was obtained from JCHR-JAEB center for health research which was coordinating center. The study was carried out in seven clinical centers (Sansum Diabetes Research Institute; USA, Montpellier University Hospital; France, Shafer Institute for Endocrinology and Diabetes; National Centre for Childhood Diabetes; Schneider Children's Medical Centre of Israel; Sackler Faculty of Medicine; Israel, Barbara Davis Centre for Childhood Diabetes; Colorado) where ethical clearance was approved by respective review boards. The written informed consent was obtained from each patient or parent, with assent obtained as required. The full protocol is available online (www.clinicaltrials.gov/ct2/show/NCT01271023).The study is designed and conducted according to ethical principles that comply with in the Declaration of Helenski. In this work, patient data anonymization was strictly performed by omitting the patient's name, address, and other personal details. The dataset for the proposed work was created considering the datetime and glucose values. Following are the study protocols followed by JDRF and the proposed work:

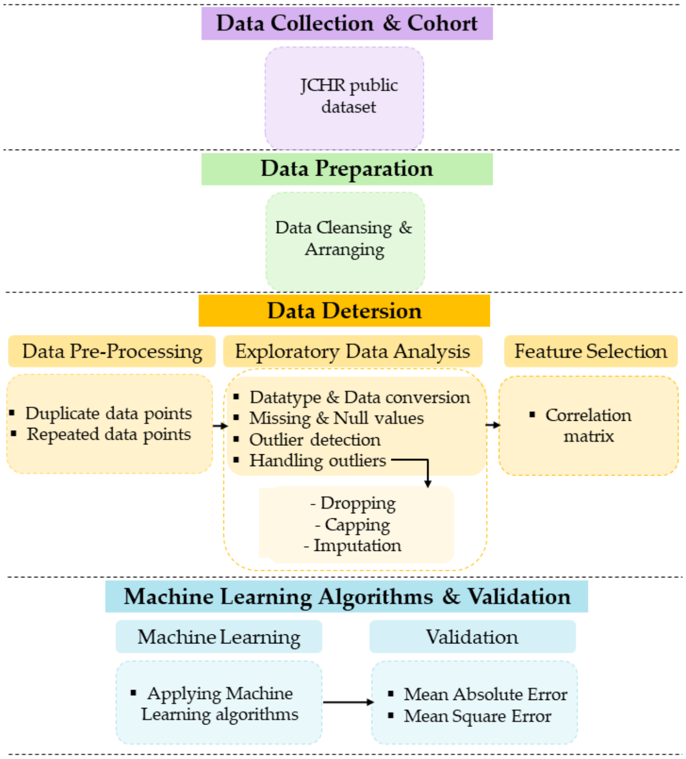


Fig. 1. Flow chart of data analyzation.

1) Eligibility: Clinically diagnosed T1DM patients for at least one year and using insulin pumps for at least six months are chosen for this study because the majority of TIDM patients are required to be on insulin pumps on a daily basis whereas T2DM and Gestational DM patients consume oral medications for regulating blood glucose levels. Patients with proper mental health and cognition for the study are chosen.

2) Sample size: In this work, sample size is chosen based on the patients whose blood glucose levels were improved. Many studies have chosen sample sizes of 13,20,25,56 [6,10,16-18] to predict insulin dosage. Therefore, glucose values at the time of bolus infusion, meal time, and amount of insulin dosage given are focused on a total sample size of 60 patients.

3) Inclusion and exclusion criteria: The inclusion criteria for this study are male and female groups aged 12 to 63 years who were on insulin pumps and CGM sensors without any break. Other age groups discontinued the treatment, and few were from the exclusion criteria. Pregnant and lactating women are excluded. Patients with diabetic ketoacidosis in the last six months, patients with Hypoglycemic episodes with unconsciousness, seizure disorder, and patients who have Coronary artery disease, active infection, muscular condition, and Cystic fibrosis are excluded due to the possibility of potential bias. The patient's name, address, and other personal particulars are entirely omitted.

B. Data Preparation

The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may note peculiarities. For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations. Data from rapid-acting insulin type is considered in this work. A similar meal size is given to all the patients during lunch, breakfast, and dinner time. Bolus insulin dosage is given before 15 minutes of meal intake. Blood glucose levels are noted. In data preparation, features required for this work are selected from Dataset1. An instance of Dataset1 is presented in Table I. The dataset consists of P.ID, Age, Sex, BMI, CBG, bolus insulin given, bolus date time (Bdt), NBG, CR, CF, and Basal Infusion (BI) as features. NBG is the blood glucose value collected after 30 min and 60 min of bolus infusion. NBG and CBG are noted for every mealtime, i.e., breakfast, lunch, and dinner time. The shaded portion in the table depicts a record of a patient whose condition improved after bolus insulin treatment. The records where the blood glucose levels are improved (all shaded portion of the dataset) after 30 min of bolus infusion are chosen and created in a separate dataset, i.e., Dataset 2.A total of eight features, i.e., Age, Sex, BMI, CBG, bolus infused, NBG, CR, and CF, are selected from Dataset1 and created into Dataset2. The features are selected based on the previous works [5, 10-11,13-14,17-18] that align with predicting bolus insulin dosage for further processing.

C. Data pre-processing, Exploratory Data Analysis, and Feature Selection

Data pre-processing, EDA, and feature selection are executed on Dataset2 by implementing Python software.

1) Data pre-processing: Data pre-processing is the next step after data collection [19,20-21]. At this step, duplicate/repeated data points are removed. In this work, Dataset 2 is checked for duplicate and repeated values at each row. No duplicates or repeated values are found in Dataset2. Therefore, EDA is applied to the dataset.

2) Exploratory data analysis: ML models perform best after applying EDA on the dataset [19,22-23]. Therefore, in this work, EDA is considered the next step after data collection and pre-processing. The primary objective of EDA is to test the data for the nature of data distribution, outliers, anomalies, and complexity. It is a tool to visualize the data for manipulation. It helps in developing parsimonious models and implements clinically relevant variables [19,22]. EDA is applied on Dataset2, where the following steps are implemented:

TABLE I. AN INSTANCE OF DATASET1 CONSTRUCTED

P.ID	Age	Sex	BMI	Bolus Insulin at Breakfast					Bolus Insulin at Lunch					Bolus Insulin at Dinner					Carbohydrate Ratio	Correction Factor
				CBG	Bolus	Bdt	NBG (30min)	NBG (60min)	CBG	Bolus	Bdt	NBG (30min)	NBG (60min)	CBG	Bolus	Bdt	NBG (30min)	NBG (60min)		
4	39	M	33.7564	154	4.25	07-05-2011 9:47:35	110	92	200	2.35	07-05-2011 11:10:42	262	270	145	3.55	07-05-2011 19:07:41	134	129	7	90
12	*40*	*F*	*27.8896*	*134*	*11.25*	*14-06-2012 8:59:46*	*174*	*217*	*379*	*0.35*	*14-06-2012 13:07:10*	*298*	*200*	*110*	*11*	*14-06-2012 19:10:23*	*119*	*110*	*13*	*27*
25	*32*	*M*	*21.9612*	*128*	*4.4*	*01-04-2012 9:00:19*	*115*	*166*	*185*	*4.3*	*01-04-2012 13:01:06*	*182*	*195*	*130*	*4.25*	*01-04-2012 19:01:16*	*119*	*110*	*12*	*20*

P.ID=patient ID;BMI=body mass index;CBG=current blood glucose;Bdt=bolus datetime;NBG=next blood glucose;

a) Datatype and data conversion: The 'Sex' attribute is converted into an integer for ease of analysis. The data type and description of the dataset are thoroughly visualized. The dataset consists of float64 and int64 datatypes suitable for further processing.

b) Identifying missing / null values: The dataset was created by eliminating inactive sensor readings; therefore, null values are not found in the dataset. If a dataset consists of null values, they must be filled by calculating the mean for numerical data and mode for categorical data.

c) Detecting outliers: Outliers are data entry errors, measurement errors, experimental errors, and sampling errors. Outliers are detected using the Interquartile range (IQR) visualization method [24-25]. The Dataset2 is checked for outliers for each feature. Outliers are found at NBG and CBG values. Boxplots for CBG and NBG are depicted in Fig. 2. Outliers detected are detailed in Table IV. It can be observed from Fig. 2(a) that CBG consists of five outliers with a max outlier value of CBG at 383 for patients aged 52 and a min outlier value of CBG at 280 for patients aged 45 as detailed in Table II. It can be observed from Fig. 2(b) that NBG consists of four outliers with a max outlier value of NBG at 370 for a patient aged 52 and a min outlier value of NBG at 268 for a patient aged 12 as detailed in Table II.

IQR is calculated as,

$$IQR = Q3 - Q1 \tag{1}$$

where,

IQR=Interquartile range, Q3=third quartile representing 75th percentile, Q1=first quartile representing 25th percentile

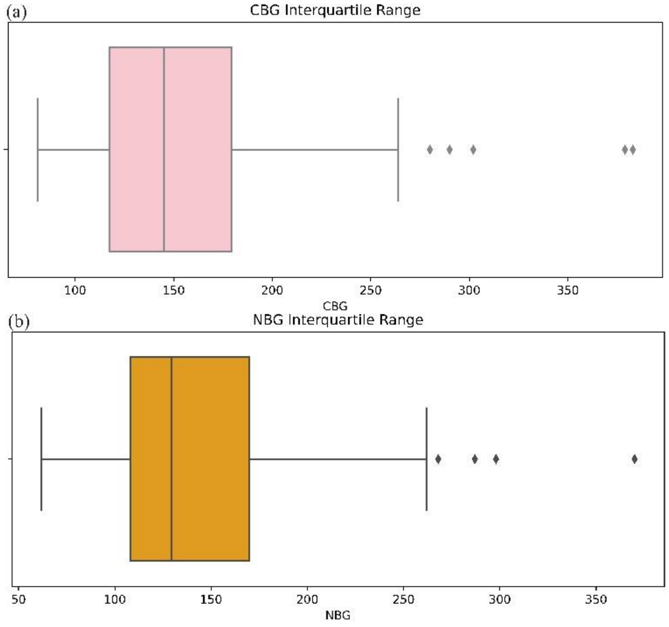


Fig. 2. Outlier detection using the IQR method. (a) Outlier detection in the CBG; (b) Outlier detection in the NBG.

The formula for the outer boundary limit is calculated as,

$$UBL = Q3 + (1.5 \times IQR) \tag{2}$$

$$LBL = Q1 - (1.5 \times IQR) \tag{3}$$

where,

UBL= Upper Boundary Limit, LBL= Lower Boundary Limit,1.5 is the decision range closer to the Gaussian distribution of outlier detection [30].

TABLE II. OUTLIER DETECTED FROM THE DATASET2

Attribute	No.of outliers	Max outlier value	Min outlier value
CBG	5	383 at age 52	280 at age 45
NBG	4	370 at age 52	268 at age 12

CBG=current blood glucose; NBG=next blood glucose

- Handling the outliers: The outliers are handled by considering the lower limit and upper limit boundaries from Eq. (6) and Eq. (7). The outliers are handled by three methods, i.e., dropping the outliers, capping the outliers, and imputing the outliers [26-27]. All approaches are applied on the Dataset2.
- Dropping the outliers: Outliers are dropped in this method. It is done by replacing outliers with a null value to differentiate from other data, and the null values are dropped. In this work, the outliers in the Dataset2 are first transformed into null values. The null values are then dropped from the dataset. A separate dataset ' droppedDataset2' file is created.
- Capping the outliers: The outliers are capped by setting a limit in the dataset. Capped values replace outliers identified above the upper limit and below the lower limit. The upper limit and lower limit is calculated from Eq. (4) and Eq. (5) as,

$$CUL = M + (3 \times SD) \tag{4}$$

$$CLL = M - (3 \times SD) \tag{5}$$

where,

CUL= Capping Upper Limit, CLL=Capping Lower Limit, M=Mean

Capped values on Dataset2 are detailed in Table III. It can be observed from Table III that on Dataset2, the lower limit for capped value is -41.69 for CBG and -46.69 for NBG. Any value falling below the lower limit will be capped at -41.64 for CBG, and -46.69 for NBG. Similarly, any value falling above the upper limit is capped at 362.67 for CBG 341.14 for NBG. The outliers from Dataset2 are capped, and a separate dataset is created as 'cappedDataset2'.

TABLE III. CAPPING OUTLIERS ON DATASET2

Attribute	Capped lower limit value	Capped upper limit value
CBG	-41.64	362.67
NBG	-46.69	341.14

CBG=current blood glucose; NBG=next blood glucose

- Imputing the outliers: The imputation of outliers is carried out by identifying the upper and lower limits in the dataset. The mean value of the feature in the dataset replaces outliers found above the upper limit and below the lower limit. The upper limit and lower limit is calculated from Eq. (6) and Eq. (7) as,

$$UL = Dataset2 > [Q3 + (1.5 \times IQR).max()] \tag{6}$$

$$LL = Dataset2 > [Q3 - (1.5 \times IQR).min()] \tag{7}$$

where,

UL=Upper Limit, LL=Lower limit

TABLE IV. IMPUTING OUTLIERS ON DATASET2

Attribute	Mean value
CBG	140.35
NBG	126.86

CBG=current blood glucose; NBG=next blood glucose

Imputed values from Dataset2 can be observed in Table IV. It can be inferred from Table IV that any value falling above the upper limit and below the lower limit is imputed by mean value, i.e., 140.35 for CBG and 126.86 for NBG. A separate dataset 'imputedDataset2' file is created.

Further analysis is carried out on the three separately created datasets, i.e., droppedDataset2, cappedDataset2, and imputedDataset2.

Feature Selection: After applying EDA on droppedDataset2, cappedDataset2, and imputedDataset2, important features are chosen to increase the performance of a model. At this step, features are selected by implementing a heatmap correlation matrix. This work implements a correlation matrix for finding the related features and patterns in a dataset. The features are highly correlated if the heatmap value is close to 1 [28]. It can be visualized from Fig. 3(a), 3(b), and 3(c) that CBG and NBG are highly correlated, whereas bolus is the target variable. Hence, CBG, NBG, and bolus are selected features from the correlation matrix and CR from [10]. ANN is applied to the dataset to test the correlation matrix's performance. It can be observed from Table V that before using feature selection, MAE of 3.12 and MSE of 17.52 were obtained with ANN. Similarly, after applying feature selection, an MAE of 1.88 and MSE of 4.78 are achieved. An improvement of 39.7% on MAE and 36.9% is observed on the dataset after applying Feature selection. The droppedDataset2, cappedDataset2, and imputedDataset2 are refined by dropping uncorrelated features, i.e., Age, Sex, BMI, CF, and by selecting CBG, NBG, Bolus, and CR.

3) Choosing the Machine Learning Model: In a few studies, LR and logistic regression are implemented [29,12], whereas other notable models such as SVR, RF, RR, LAR, and gradient boosting are explored [5,9,11,29]. Some literature has explored ensemble methods, i.e., bagging, boosting, and DT [10] and ANN [10,12,13,14]. It was inferred from the studies that the performance of the ML algorithm depends on the type of the dataset and methodologies [5-14]. Therefore, in this proposed work, k-NN, k-NN bagging, k-NN boosting, DT, DT bagging, DT boosting, and ANN are compared for validation.

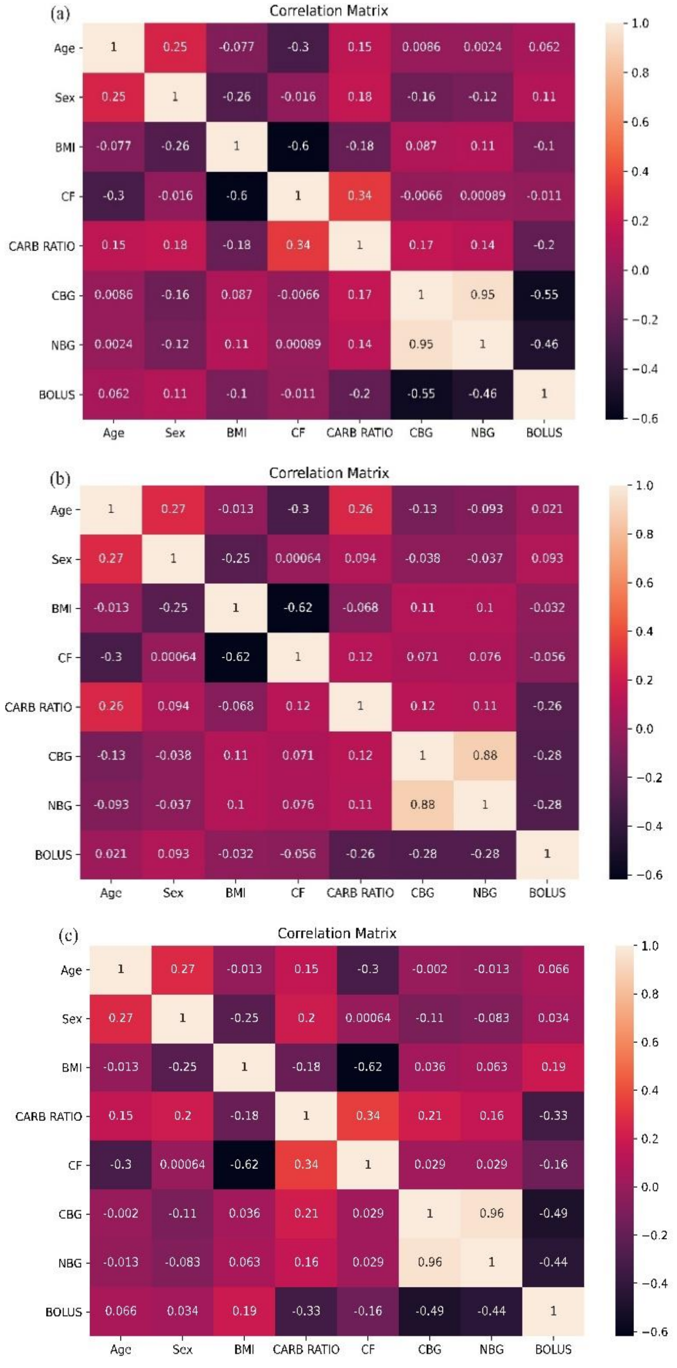


Fig. 3. Correlation matrix. heatmap of (a) Droppeddataset2; (b) Cappeddataset2; (c) Imputeddataset2.

TABLE V. PERFORMANCE METRICS OF ARTIFICIAL NEURAL NETWORKS BEFORE AND AFTER FEATURE SELECTION ON DATASET2

Dataset	MAE	MSE
Before Feature Selection	3.12	17.52
After Feature Selection	1.88	4.78

MAE=mean absolute error; MSE=mean squared error

III. RESULTS AND DISCUSSION

This section presents the results for predicting bolus insulin by applying ML algorithms on curated datasets, i.e., droppedDataset2, cappedDataset2, and imputedDataset2.

A. *Bolus Insulin Prediction Based on Current Blood Glucose and Improved Next Blood Glucose Levels*

The process flow of the work is depicted in Fig. 4. All three datasets are subjected to different ML algorithms for predicting bolus insulin. The models are validated by evaluating MAE and MSE. The performance of each dataset is compared with a recent work carried out to predict insulin [10].

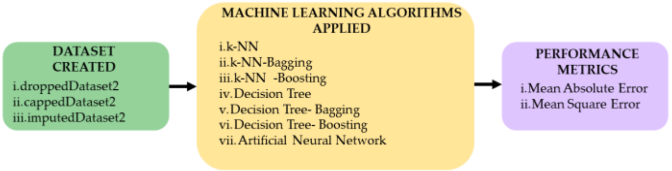


Fig. 4. Illustration of pipelines from dataset, machine learning algorithms and performance metrics.

1) Performance Metrics on Data Detersion Applied Models: Metrics implemented to measure the curated models are MAE and MSE. Absolute Error (AE) is the difference between the target and the predicted value, as mentioned in Eq. (8). MAE is an average of AE, as mentioned in Eq. (9). Squared error (SE) is the difference between the square of the target and the predicted value. MSE is the average mean of SE as mentioned in Eq. (10). The performance metrics are given as,

$$AE = \left|BI_{pred} - BI_{tgt}\right| \tag{8}$$

$$MAE = \frac{1}{M}\sum_{I=1}^{M}\left|BI_{pred} - BI_{tgt}\right| \tag{9}$$

$$MSE = \frac{1}{M}\sum_{i=1}^{M}\left|BI_{tgt} - BI_{pred}\right|^{2} \tag{10}$$

where,

BI =Bolus insulin, M = number of observations, BI_{pred}= predicted bolus insulin level, BI_{tgt}= target bolus insulin level.

2) Predictive Analysis: The dataset consists of 60 samples where CR, CBG, NBG, and Bolus Insulin are considered as input features. The ML models are trained by splitting the dataset into 80% for training and 20% for testing. ML algorithms are applied to the dataset before and after implementing feature selection. It can be inferred from Table VI that the performance metrics are high before feature selection, and the dataset performed the best with an MAE of 1.88 and MSE of 4.78 after feature selection.

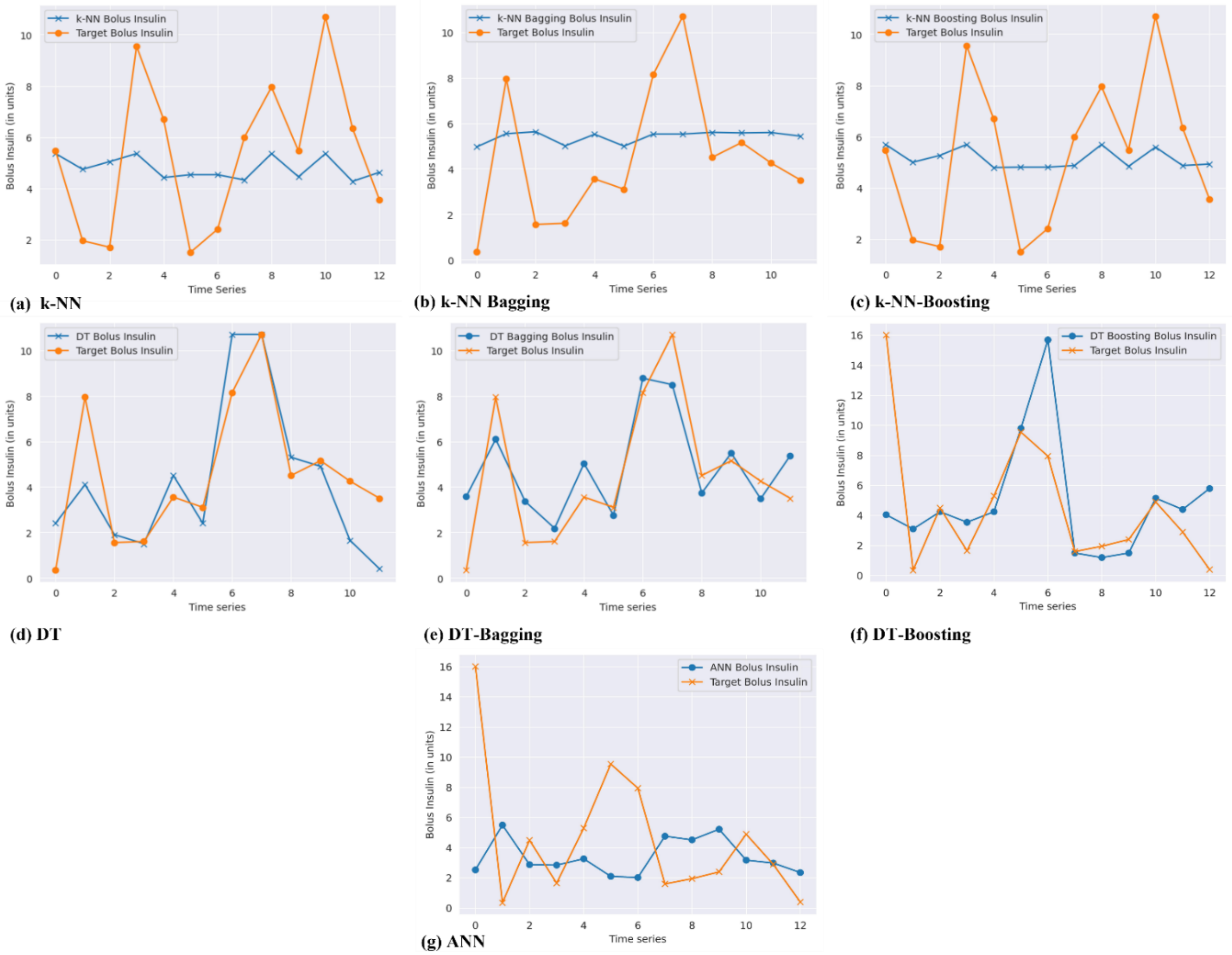
K-NN is a regression algorithm where the predicted dependent variable is the average of k-nearest neighbors [30]. k-NN is applied to the curated datasets. Total neighbors, i.e., n_neighbors=21, are considered with 'uniform weights, 'brute' algorithm, and 'Minkowski' tree metric with power 'p=2'. imputedDataset2 performed best with MAE as 2.43 and MSE as 7.40 when compared with droppedDataset2 where MAE as

2.40, MSE as 8.08, and cappedDataset2 with MAE as 2.61, MSE as 10.47 is achieved. A difference in the trend of target and predicted bolus insulin can be observed in Fig. 5(a). Therefore, the model cannot be recommended for prediction of bolus insulin.

TABLE VI. ANALYSIS OF CALIBRATION ON DIFFERENT MODELS

Reference		Machine Learning Algorithms							
		Metrics	*k-NN*	*k-NN -Bagging*	*k-NN -Boosting*	*DT*	*DT-Bagging*	*DT-Boosting*	*ANN*
Recent work [23]		MAE	2.33	2.36	2.40	2.57	2.41	2.45	**2.12**
		MSE	6.47	6.65	7.16	11.35	8.59	10.66	**5.79**
Proposed Work									
Before Feature Selection		MAE	3.06	2.95	3.85	2.42	2.03	**2.34**	3.12
		MSE	14.59	14.04	18.47	13.41	12.52	**12.14**	17.52
After Feature Selection		MAE	2.51	2.51	2.54	2.62	2.48	2.11	**1.88**
		MSE	8.39	8.20	8.45	13.41	7.28	11.51	**4.78**
Data Detersion Applied	droppedDataset2	MAE	2.40	2.34	2.33	2.06	2.10	2.19	**1.64**
		MSE	8.08	6.53	7.48	6.59	7.16	9.67	**4.16**
	cappedDataset2	MAE	2.61	2.63	2.80	2.39	**1.54**	2.13	3.65
		MSE	10.47	10.10	10.28	18.96	**4.15**	8.22	18.69
	imputedDataset2	MAE	2.43	2.63	**2.33**	**2.04**	2.12	2.22	2.75
		MSE	7.40	9.73	**7.25**	**5.13**	7.51	10.26	11.75

MAE=mean absolute error; MSE=mean squared error; DT=decision tree; ANN=artificial neural network



(a) k-NN

(b) k-NN Bagging

(c) k-NN-Boosting

(d) DT

(e) DT-Bagging

(f) DT-Boosting

(g) ANN

Fig. 5. Target and predicted bolus insulin from different models, I.E., (a) K-NN (b) K-NN Bagging (c) K-NN Boosting (d) DT (e) DT-Bagging (f) DT-Boosting (g) ANN.

K-NN with the Bagging-Ensemble algorithm combines two or more models [30]. A bagging regressor is applied on k-NN where the dataset is divided into many subsets, and the model is fitted on each subset independently. Predictions are made by aggregating individual predictions on the subsets [31-32]. K-NN is the base estimator with n_estimators=20. K-NN Bagging is applied on the curated datasets where droppedDataset2 performed best with MAE of 2.34, MSE of 6.53 when compared to the cappedDataset2 with MAE of 2.63, MSE of 10.10 and imputedDataset2 with MAE of 2.63, MSE of 9.73. droppedDataset2 performed best among curated datasets and even with comparison to recent work on predicting insulin [10]. The pattern of target and predicted bolus insulin on droppedDataset2 with k-NN Bagging can be observed in Fig. 5(b). It can be inferred that with an MAE of 2.34 and MSE of 6.53, the pattern of k-NN bagging is similar to k-NN with a decrease of 0.1 in MAE and a 0.87 increase in MSE. Differences can be observed between target and predicted bolus insulin. Therefore, this model cannot be recommended to predict bolus insulin.

K-NN with Boosting is an ensemble learning model learned from previous mistakes of weak classifiers sequentially [30]. The advantage of the model is to tune the weak into a robust model. It is an iterative method of increasing the efficiency of binary classifiers [31-32]. The base estimator is k-NN with n_estimators=100, a learning_rate of 0.3, and a 'square' loss. k-NN Boosting is applied on the curated datasets where imputedDataset2 performed best with MAE of 2.33 and MSE of 7.25 when compared to droppedDataset2 with MAE of 2.33, MSE of 7.48, and cappedDataset2 with MAE of 2.80, MSE of 10.28. The imputedDataset2 performed best in MAE with an increase of 0.9 in MSE when compared to [10]. The trend of target and predicted bolus insulin on imputedDataset2 can be observed in Fig. 5(c), where the pattern of target and predicted bolus insulin is similar to k-NN and k-NN Bagging. Therefore, this algorithm cannot be suggested for the prediction of bolus insulin.

DT model utilizes a set of binary rules to evaluate target value. Each tree has a simple model with branches, nodes, and leaves [33]. DT is applied on the curated datasets, i.e., where droppedDataset2 performed the best with MAE of 2.39, MSE of 18.96, and imputedDataset2 with MAE of 2.04, MSE of 9.13. droppedDataset2 performed best when compared to [10]. It can be inferred from Fig. 5(d) that the pattern of target and predicted bolus insulin performed better than other datasets. Therefore, it can be considered for the prediction of bolus insulin.

DT Model with Bagging is an ensemble model with DT as the base estimator where n_estimators=20.Bagging is applied on the curated datasets where the cappedDataset2 performed the best with MAE of 1.54 and MSE of 4.15 when compared to droppedDataset2 with MAE of 2.10 and MSE of 7.16 and imputedDataset2 with MAE of 2.12 and MSE of 7.51. Curated datasets performed the best compared to recent work on predicting insulin [10]. It can be inferred from Fig. 5(e), with MAE of 1.54 and MSE of 4.15, that the target and predicted bolus insulin follow a pattern. DT model with bagging can be implemented for predicting real-time insulin levels. This prediction is supportive of insulin pump therapy with minimum error.

DT Model with Boosting is an ensemble model with DT as the base estimator where n_estimators=20. Boosting is applied on DT to the curated datasets where capped Dataset2 performed best with MAE of 2.13 and MSE of 8.22 when compared to droppedDataset2 with MAE of 2.19 and MSE of 9.67, and imputedDataset2 with MAE of 2.22 and MSE of 10.26. The curated dataset performed better when compared to recent work [10]. It can be inferred from Fig. 5(f) that the model has a similar pattern to DT-Bagging, with an increase of 0.59 in MAE and 4.07 in MSE. As the former model, i.e., DT-Bagging, performs better than DT-Boosting, the former model can be considered for bolus insulin prediction.

ANN is applied where input dimensions of four, kernel initializer as 'normal' and 'relu' activation layer is considered. Hidden layers of 10 are considered with an epoch of 1000, batch size of 50, and verbose of 1. ANN is applied on the curated datasets where MAE and MSE obtained on droppedDataset2 are 1.64 and 4.16, performing the best compared to recent work [10]. MAE, MSE obtained on droppedDataset2 is 3.65, 18.69, and MAE, MSE obtained on imputedDataset2 is 2.75, 11.75. It can be observed from Fig. 5(g) that droppedDataset2 performed best when compared with cappedDataset2 and imputedDataset2. Due to the higher MAE and MSE of the ANN algorithm than DT with bagging, this model cannot be implemented for real-time prediction of bolus insulin.

DT with bagging performed the best with an MAE of 1.54 and MSE of 4.15. This model is recommended for predicting bolus insulin in real time. The findings of the proposed work are: (i) Feature selection plays a significant role in enhancing the performance of the dataset. An improvement of 39.7% (from 3.12 to 1.88) in MAE and 72.7% (from 17.52 to 4.78) in MSE with ANN is achieved after applying Feature Selection. (ii) The model's performance is enhanced with the data detersion process, where an improvement of 47.4% (from 3.12 to 1.64) in MAE and 76.2% (from 17.52 to 4.16) in MSE with the ANN model. (iii) Applying bagging and boosting enhanced the dataset's performance compared to non-bagging and boosting models. An improvement of 35.5% in MAE (from 2.39 to 1.54) and 78.1% MSE (from 18.96 to 4.15) with DT-Bagging is achieved. Similarly, 10% in MAE (from 2.39 to 2.13) and 56.6% MSE (from 18.96 to 8.22) with DT-Boosting is achieved. Therefore, it can be implied that the integration of AI and data science for the data detersion process boosts the performance of the models. The validation of the DT-Bagging model on cappedDataset2 is presented in the further section.

3) Validation of DT- Bagging Model: Bagging is an ensemble method combining several decision trees to optimize performance. DT with bagging architecture is presented in Fig. 6. The training dataset 'T_r'is divided into several subsets of data, i.e., $T_{1......}$ T_n which can be chosen randomly with replacement. Multiple learning models are generated by training each learner in the ensemble structure with the subsets. The subset of data is implemented for training the decision tree. Prediction from each DT model, i.e.,

$DT\ Model_1\ DT\ Model_n$ are aggregated, and insulin dosage is finally predicted. DT-Bagging is derived in Eq. (11).

$$p(o) = \frac{1}{B_P}\sum_{n=1}^{B_p} p_n\,(o) \qquad (11)$$

where,

$p(o)$ =predicted output, B_P =bootstrapping sets,$p_n(o)$=weak learners

The plot against the target and predicted bolus insulin is depicted in Fig. 7. The X-axis represents the target bolus insulin, whereas the Y-axis represents the predicted bolus insulin. It can be inferred that the target and predicted bolus insulin data points are closer to the trendline, defining a high correlation. DT-Bagging is validated by performing an error analysis. Error analysis evaluates MAE between the target and predicted insulin levels, as illustrated in Table VII. The model is tested with a new dataset of 20 samples where 13 samples are tabulated in Table VII. It can be inferred that the maximum variance achieved is 2.49, and the minimum variance is 0.08, falling under the tolerance limit of ±5 from IEC60601-2-12 of insulin pump protocol [34]. As the performance of the model with MAE of 1.50 is in the clinically acceptable range, the developed model is suitable for deploying insulin pumps.

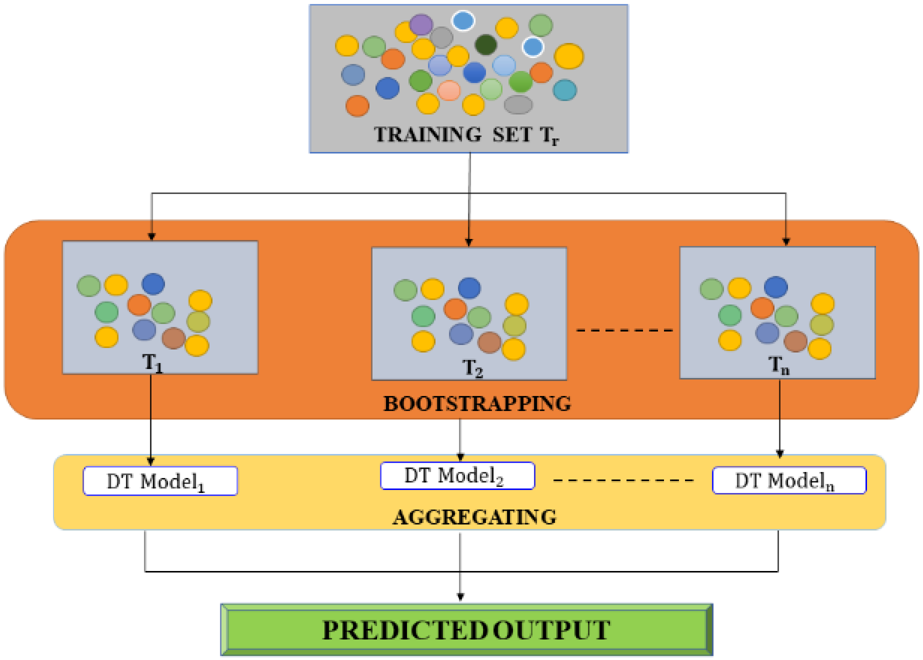


Fig. 6. Decision tree-bagging architecture.

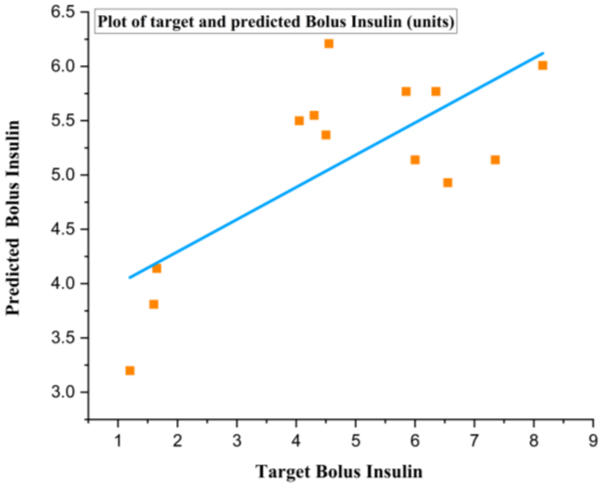


Fig. 7. The plot of target and predicted insulin levels on the proposed data detersion process on logcappeddataset2.

The proposed study is compared with previous approaches to insulin prediction in Table VIII. All the datasets curated from the data detersion process obtained the best performance with MAE and MSE compared to previous literature [9-11, 13].

The data detersion process proposed in the current work obtained the best performance with an MAE of 1.50 and MSE of 4.15.

The implications of the study outcomes are to make informed clinical decisions, treatment titrations, changes in lifestyle habits, and evidence-based dosage recommendations. It can be applied at the development stage of insulin clinical trials and drug dosage.

The model can be deployed in an insulin pump and can be integrated with the CGM device. Insulin dosage can be predicted in real-time based on blood glucose levels. The model can be deployed with a customized regimen considering an individual's health conditions and physical activity. The likelihood of successful outcomes due to improvement in treatment efficacy can be expected from the model's performance in bolus insulin prediction. Therefore, with the proposed work, adverse side effects such as hyperglycemia and hypoglycemia can be controlled, and balanced blood glucose levels can be achieved with better diabetes management.

TABLE VII. VALIDATION OF PROPOSED DATA DETERSION ON CAPPEDDATASET2

Target Insulin ($\boldsymbol{BI_{tgt}}$) units	Predicted Insulin ($\boldsymbol{BI_{pred}}$) units	Absolute Error$\boldsymbol{\lvert BI_{pred} - BI_{tgt}\rvert}$ units
6	5.14	0.86
5.85	5.77	0.08
6.35	5.77	0.58
1.65	4.14	2.49
8.15	6.01	2.14
4.05	5.5	1.45
1.6	3.81	2.21
7.35	5.14	2.21
6.55	4.93	1.62
4.3	5.55	1.25
4.55	6.21	1.66
4.5	5.37	0.87
1.2	3.2	2
Mean Absolute Error (MAE) $\frac{1}{N}\sum_{I=1}^{N}\lvert BG_{pred} - BG_{tgt}\rvert$		1.50

BG_{pred}=predicted blood glucose; BG_{tgt}=target blood glucose

TABLE VIII. COMPARISON OF NON-INVASIVE APPROACHES IN NIR-SPECTROSCOPY WITH THE CURRENT STUDY

Reference	**Data Detersion Applied**	**Methodology**	**Performance Metrics**
Liu et al.[21]	No	Random Forest	MAE=4.1
Y.Obeidat, et al.[23]	k-NN Imputation	ANN	MAE=5.79
Nguyen et al.[24]	No	Ensemble Machine Learning algorithm	MAE=12
Zahran et al.[26]	No	ANN	Prediction error=4%
Proposed Work			

droppedDataset 2	Dropping	ANN	MAE=1.64
			MSE=4.16

logcappedDatas et2	Capping	DT-Bagging	MAE=1.54
			MSE=4.15

imputedDataset 2	Imputation	k-NN-Bagging	MAE=2.12
			MSE=7.51

ANN=artificial neural network

IV. CONCLUSION

The strength of the proposed work is in (i) Bolus insulin prediction from CBG and improved NBG from previous literature are implemented in the current study [23]. (ii) Feature Selection is done to select correlating features between independent and dependent variables. An improvement of 37.9% is observed before and after applying Feature Selection on MAE and MSE from the DT-Bagging algorithm. (iii) Implementing Bagging on DT has improved the performance by 15% in both MAE and MSE, thus enhancing the model's performance. To understand the performance of the original dataset, ML algorithms are applied after which feature engineering is implemented. This attempt was to analyze if feature engineering could make any improvement in the prediction. To improve the performance after feature engineering, the original dataset was subjected to three ways of data detersion process to cure the data on which ML algorithms are applied. The limitation of the proposed work is the size of the dataset created. As CBG and improved NBG are considered from the dataset of 24,170 rows of bolus infusion, only 60 data showed improvement in NBG levels. Therefore, the model is built on a small dataset of size 60. To deploy the algorithm in a real-time scenario in an insulin pump, uncertainties and artifacts such as integration with CGM device and other health complications. The study is conducted only on T1DM with insulin pumps of at least six months and excluded patients with Diabetic and Coronary disease complications, making the proposed study less generalizable to a large population. Future work is to create a model on the massive dataset by considering CBG and improved NBG levels from different public datasets and predict bolus insulin dosage.

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Cross-Modal Video Retrieval Model Based on Video-Text Dual Alignment

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***Abstract*—Cross-modal video retrieval remains a major challenge in natural language processing due to the natural semantic divide between video and text. Most approaches use a single encoder to extract video and text features separately, and train video-text pairs by means of contrastive learning, but this global alignment of video and text is prone to neglecting more fine-grained features of both. In addition, some studies focus only on profiling the video description text, ignoring the correlation relationship with the video. Therefore, this paper proposes a video retrieval method based on video-text alignment, which realizes both global and fine-grained alignment between video and text. For global alignment, the video and text are aligned by a single encoder and after linear projection; for fine-grained alignment, the video encoder is trained to align the video and text by masking some semantic information in the text. By experimentally comparing with multiple existing methods on MSR-VTT and MSVD datasets, the model achieves R@1 (recall at 1) metrics of 51.5% and 52.4% on MSR-VTT and MSVD datasets, respectively, which indicates that the proposed model can improve the efficiency of cross-modal video retrieval.**

Keywords—Video-text alignment; cross-modal; contrastive learning; similarity measure; feature fusion

I. INTRODUCTION

With the proliferation of mobile devices and high-speed networks, network resources predominantly manifest in textual and video formats. Video's formidable capacity for conveying information confers upon it a distinct advantage, rendering it more popular among users. Video retrieval not only reduces costs but also fosters innovation, enhances the quality of life, and generates economic value in diverse fields such as education, military, and healthcare. Consequently, the demand for precision in video content retrieval is escalating, making the enhancement of video retrieval efficiency a formidable research pursuit. Within the realm of video comprehension, a natural semantic gap exists between the various modalities of video. Solely extracting semantic features from videos is susceptible to yielding sparse feature representations, consequently diminishing the accuracy of video retrieval. Consequently, numerous scholars have endeavored to represent video features through multiple modalities to augment the precision of video retrieval, yielding noteworthy results. Current models such as Frozen [1], CLIP4Clip [2], and Clipbert [3] use contrast learning to achieve semantic alignment and interaction of cross-modal features, where features from different modalities are extracted and then mapped into the same space, enabling global alignment of video with video description text.

The semantic alignment strategy for unimodal encoders in comparative learning typically involves the integration of features from video description text and video features to calculate their similarity. However, this approach often overlooks the association between the local features of the two modalities, resulting in asymmetry in their representation and impacting the efficiency of cross-modal retrieval. In addressing these issues, some researchers employ lexical embedding [4] to achieve fine-grained retrieval by leveraging the relationship between different lexemes. Chen et al. [5] introduced a hierarchical graph inference model to generate text embeddings using an attention-based graph inference mechanism, capturing global-to-local feature associations. Notably, this model primarily focuses on text comprehension and neglects alignment with video content. To address this limitation, HANet [6] enhances the alignment between video and text by introducing a word-level attention mechanism. This mechanism calculates the importance of each word in the video representation and weights the text representation accordingly. However, the computational complexity of HANet is high due to the incorporation of a multi-level attention mechanism.

Upon a thorough examination of relevant research, it becomes evident that video retrieval models should prioritize video sub-regions closely associated with a given video summary. This entails employing cross-modal reasoning between video summaries and video frames to identify the most semantically relevant segments in both, thereby achieving alignment between the video and the summary text. However, prevailing video retrieval models frequently rely on global features of videos, utilizing mean pooling or self-attention methods. Unfortunately, these approaches fall short in effectively integrating the concept of cross-modal reasoning in practical applications. Consequently, the lack of fine-grained semantic attention to both video and summary text within the global alignment model hinders the encoding of localized visual information in the video. This deficiency subsequently leads to a degradation in retrieval performance.

In this paper, we introduce a dual video-text alignment model that aims to narrow the semantic gap between video and text at a finer granularity, thus improving the efficiency of video retrieval. Initially, a conventional methodology is employed to map features from both the video and the summary text into a shared space. This facilitates the computation of contrast loss, thereby achieving global alignment between the video and the text. Subsequently, we concentrate on the actions or scenes involving entities in the video, aligning them with the nouns and verbs present in the

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textual description. This dual-pronged approach not only establishes global alignment but also enables more refined local alignment. The result is a comprehensive interaction between video and text, enhancing retrieval performance.

The rest of this paper is as follows, Section II review previous studies. Section III discusses the methodology. Section IV presents experimental setup. Section V describes the results of the experiment and discusses. Finally, conclusion presents in Section VI.

II. Related Works

This section provides an overview of related work on video retrieval methods and the video-text alignment method used in this paper, where exploring a new video retrieval method is the target task of this paper, and the study of the video-text alignment method is the focus of this paper.

A. Video Search Methods

Video-text alignment methods are more commonly used in video retrieval tasks. In their earlier work, Kaufman et al. [7] focused on pre-training by designing cross-modal fusion mechanisms, utilizing large-scale multimodal data for pre-training, and fine-tuning in downstream tasks. However, these approaches usually focus only on the global alignment of video and text, ignoring the interaction of local representations and affecting the retrieval efficiency.

Currently, popular methods encode video and text into feature vectors that are projected into a common space for matching by means of a dual-encoder structure of a text encoder and a video encoder. These methods utilize dot product operations to compute the global similarity and thus achieve alignment between video and text. For example, Bain et al. [1] proposed an end-to-end model that utilizes the ideas of ViT [8] and Transformer [9] to achieve a common representation of video and text. Luo et al. [2] utilized the knowledge migration of CLIP [10] to match the feature vectors of the video and the text in the common space and retrieve them by using the similarity between the vectors. Li et al. [11] matched multiple encoders in a specific common space, avoiding the dominant role of a single encoder and failing to fully utilize the visual information within the video, relying too much on textual information. In addition, methods based on graph neural networks [12], which represent video and text as graph structures; utilize graph neural networks for information dissemination and fusion. However, these methods still have some problems:

1) Global similarity may not adequately capture the complex relationships between video and text. Since video and text have different structures and semantics, relying only on global similarity may ignore the interaction of local representations.

2) Inconsistency in the length of video and text may lead to information loss. In a dual-encoder architecture, the output of the text encoder is usually truncated to fit the input of the video encoder. This truncation may lead to loss of textual information during the encoding process, thus affecting retrieval.

3) Imbalance of training data may lead to model overfitting. In video-text retrieval tasks, the training data is usually unbalanced, which may lead to overfitting of the model to local similarities during the training process, while ignoring the importance of global similarities.

To address these problems, researchers have proposed some improvement strategies, such as introducing an attention mechanism and utilizing methods such as contrast learning to capture local and global representations between video and text, which can effectively improve the performance of video-text retrieval tasks.

B. Video-Text Alignment Methods

Video-text alignment is commonly used in application domains such as video retrieval, video annotation, and video quizzing, and using features and objects in the video to match with the text is a common alignment method. Some work relies on the attention mechanism to extract information from videos [13], which is then used in downstream tasks such as video quizzing. Wang et al. [14] utilized multiple pre-trained experts to extract multimodal information and use it as an anchor point for alignment with text. Dong et al. [15] designed dual coding networks to perform multilevel coding of video spatial and temporal information with text. Luo et al. [2] based on the inspiration of a large-scale pre-trained graphic-text matching model CLIP [10], migrated the image-text alignment method to video-text alignment to realize video text retrieval. However, all these alignment methods are global alignment on the whole of video and video description text, ignoring the finer-grained semantic information alignment between the two.

To solve the above problems, some works split text descriptions into semantic phrases, e.g., Yang et al. [16] construct a semantic tree representation of the text and use a temporal attention encoder to obtain a video representation. Wang et al. [17] manipulate a fine-grained comparison target by selecting video frames that are semantically equivalent to the text to better learn the representation of the video and the text. Chen et al. [5] extract the text from the sentence to extract verbs and nouns and project them into a shared space for fine-grained alignment. In addition, Li et al. [18] performed large-scale image-text comparison learning through the Twin Towers model, which aligns the visual information in images with the meaning of text masked words through Masked Language Model (MLM) and Image-Text Matching (ITM) to achieve image-text retrieval.

Synthesizing the research on video retrieval algorithms, this paper proposes effective solutions to the problems of the current methods in Section *A*, and the main contributions include:

1) A video-text dual alignment model is proposed to enhance the interaction of local representations by aligning the global and fine-grained features of video with those of text to capture the more complex semantic relationships between the two.

2) Using the Transformer-based dual encoder structure, text information can be encoded more comprehensively, reducing the missing information caused by truncated text features.

3) Using the contrast learning method, video features are fitted to sentence features with global and fine-grained similarity to increase the balance of the training data and improve the video retrieval accuracy.

III. Methodology

The video-text dual alignment method employs dual encoders to train video and text features, proposing a dual alignment model for both global and fine-grained alignment to enhance cross-modal alignment between videos and summary text for improved video retrieval accuracy.

In this section, Section *A* provides an overview of the model to illustrate its working principles and processes, Section *B* details how video and text features are extracted, Section *C* introduces the framework and working principles of the dual alignment network model, Section *D* outlines the model's training strategy. Finally, Sections *E* and *F* elaborate on the objective functions and pretraining datasets used in this approach.

A. Overview of the Model

As illustrated in Fig. 1, our model adopts a two-tower structure to capture semantic information from both video and text during the feature extraction phase, employing dedicated encoders for each modality. For a given set of videos, the TimeSformer [19] serves as the video feature encoder. The output features, denoted as x_i and v_i, plays crucial roles in the global and fine-grained alignment of video and text, respectively. In the case of video description text, two inputs are provided to the text encoder DistilBERT [20]: the sentence with deleted verbs and nouns, and the complete video text description. The extracted text features y_i and t_j are used for global alignment and fine-grained alignment, respectively.

During the video-text alignment phase, one branch focuses on global alignment, projecting global video and text features into a common space. This branch is trained using a contrastive learning method to attain comprehensive semantic alignment of features on a global scale. The other branch is dedicated to fine-grained alignment, achieving detailed alignment between video and text by training a multimodal encoder to acquire vector representations of deleted nouns and verbs in the video modality.

The model enhances its cross-modal alignment capability, specifically in video-text alignment, through the incorporation of a cross-modal attention mechanism. This mechanism projects both the video and text into an embedding space, where semantic similarity is maximized. Consequently, for a given text query, video retrieval is formulated as a cross-modal similarity metric, aiming to identify videos that exhibit semantic alignment with the query.

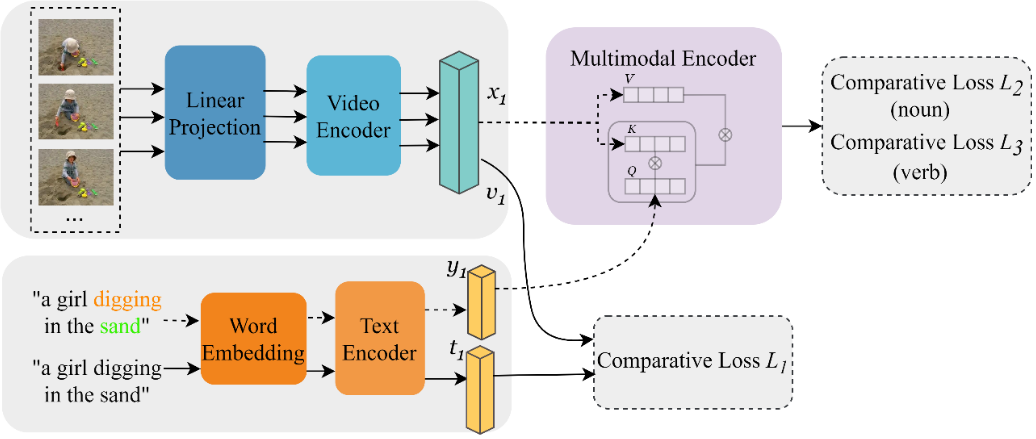


Fig. 1. Video-text dual alignment framework.

B. Feature Extraction

In this approach, both video and summary text undergo parsing using a video encoder and a text encoder. The distinct data modalities are then transformed into a unified numerical representation, yielding a sequence of feature representations for both. This facilitates alignment between the video and summary text on both a global and fine-grained level.

1) Video representation: This paper employs a dual encoder architecture for the extraction of video and text features. Specifically, TimeSformer is utilized to extract video features for each video. During the extraction of video features, as illustrated in Fig. 1, the M video frames of the clip are initially input into TimeSformer. Each video frame is then partitioned into P patches, which are subsequently fed into a linear projection header, spreading them into a series of tokens for the video. Following this, learnable $[CLS]$ tokens are affixed to the header of the sequence, enhancing our ability to learn sentence-level features for downstream tasks. Learnable positional embeddings are also introduced to the tokens. For each video frame feature $v_i \in R^{M\times P\times D}$, with D representing the feature dimension, TimeSformer applies the self-attention mechanism in both temporal and spatial dimensions, generating the final sequence of video frame embeddings $v_i = \{v_{cls}, v_1, v_2, ..., v_p\}$.

2) Text representation: For each of the N text descriptions associated with each video, this approach employs the DistilBERT model for feature extraction.

DistilBERT, being a lightweight BERT [21] model, is more suitable for deployment and operation under resource constraints due to its smaller size compared to the BERT model. DistilBERT produces a text embedding sequence, denoted as $t_j \in R^{N\times D}$, by tagging text description embeddings $[CLS]$ and positional tags, resulting in text features represented by $t_j = \{t_{cls}, t_1, t_2, ..., t_N\}$.

C. Model Framework

This paper centers on the examination of video-text alignment methods, emphasizing the double alignment of feature representations for both video and descriptive text at both global and fine-grained levels. This approach aims to enhance the overall understanding of the video and descriptive text, thereby improving the retrieval accuracy of the model.

1) Global alignment: In the context of global comparative learning, for a given video-text pair, subsequent to extracting features using two distinct encoders, the video embedding sequences and text embedding sequences are initially projected into a shared space through linear projection. Subsequently, all frames of each video undergo aggregation using mean pooling to obtain the average frame $\overline{v_i}$, $\overline{v_i} \in R^{1\times D}$. For each text, this paper extracts the representation by taking the first $[CLS]$ token, denoted as $\overline{t_j}$, $\overline{t_j} \in R^{1\times D}$. Finally, the method computes the similarity between them using the cosine similarity function denoted by $s(v_i, t_j)$. During training, the objective is to maximize the correct pairing of video-text pair comparisons while minimizing the remaining comparison targets that cannot be paired. The cosine similarity function is defined as shown in Eq. (1).

$$s(v_i, t_j) = \frac{\overline{v_i} \bullet \overline{t_j}^T}{\left\|\overline{v_i}\right\|\left\|\overline{t_j}\right\|} \qquad (1)$$

2) Fine-grained alignment: In the domain of video-text alignment, when given a video and its corresponding text description, this approach involves the removal of nouns from the text, utilizing the incomplete sentence with omitted nouns as the text to be aligned. The sentence then undergoes processing through a text encoder to obtain an intermediate text sequence representation $\{n\}_{n\_t}$. Simultaneously, the video is processed through a video encoder to acquire the intermediate video sequence representation $\{c\}_v$.

Subsequently, the linear transformation of the noun text sequence $\{n\}_{n\_t}$ is treated as the query (Q), and the linear transformation of the video sequence $\{c\}_v$ serves as keys and values (K,V). Through cross-modal attention using the Transformer, these are interacted to obtain vector representations of nouns that can be aligned in the video modal space. The nouns, removed from the text, are also processed through the text encoder to obtain a text space vector representation of the nouns, which are used to form positive and negative samples in the comparison target.

The video sequence representation and the noun sequence representation are projected through two separate linear layers into a common embedding space, and their similarity is computed using a cosine similarity function. The formulation of the cross-modal attention mechanism is depicted in Eq. (2):

$$Attention(Q,K,V) = Soft\max(\frac{QK^T}{\sqrt{d_k}})V \qquad (2)$$

where, Q denotes the text sequence originating from the deletion of the noun in the sentence, K and V denote the sequences originating from the video representation, and d_k denotes the dimension of K.

Similarly, the same operation is executed when removing a verb from a text as when omitting a noun. The sequence representation $\{v\}_{v\_t}$ of the sentence lacking the verb is derived, linearly transformed as a query (Q) in cross-modal attention, and interacted with the linear transformation of the video sequence representation $\{c\}_v$ to obtain the vector representation of the verb in the video modal space that can be aligned.

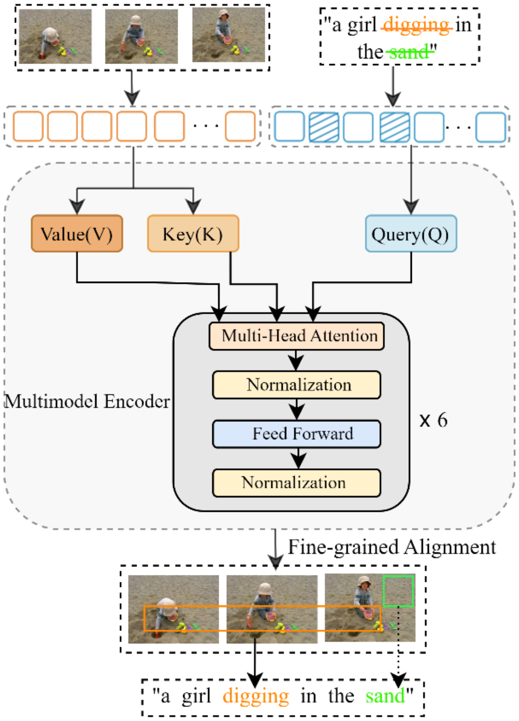


Fig. 2. Fine-grained alignment process.

The removed verbs also undergo processing through a text encoder to obtain a text space vector representation of the verb. The similarity is computed after passing these two representations through separate linear layers.

The fine-grained alignment process is depicted in Fig. 2, where this model linearly transforms the two modal features extracted from the video and the text, each with the noun or verb removed. The linearly transformed Q, K, and V are employed as inputs to the multimodal encoder, which captures cross-modal attentions between the video and the text through the multi-head attention module.

Following this, a contrast learning approach is utilized to maximize the similarity of correctly paired nouns or verbs and minimize the vice versa scenario. The training model is adept at extracting semantic information, such as scenes or actions, from the video content that aligns with the nouns or verbs in the text. This enables a higher degree of fine-grained alignment between the video and the text, consequently enhancing the efficiency of video retrieval.

D. Training Strategy

In the contrast learning model presented in this paper, it projects input samples into a low-dimensional vector space. The model undergoes initial training, ensuring that similar samples in the vector space are mapped to proximate locations, while dissimilar samples are mapped to distant locations. Specifically, for an input sample x_i and a positive sample y_i, the model is trained by maximizing their similarity. Simultaneously, within the same batch, unpaired samples are considered as negative samples. The objective is for the model not only to match positive samples but also to distinguish them from negative samples.

Throughout the training process, for the given video-text pairs, this paper employs comparison learning utilizing the loss function based on cosine similarity scores, as demonstrated in Eq. (3):

$$L_{nce} = -\sum_{i=1}^{N} log \frac{exp(\, s(x_i , y_i \,) / \tau \,)}{\sum_{i=1}^{N} exp((x_i , y_j \,) / \tau \,)} \tag{3}$$

where, $s(\, x_i , y_i \,)$ denotes the similarity score between input samples x_i and samples y_i, and N represents the batch size. The temperature coefficient τ is a hyperparameter that must be set to control how effectively the model discriminates between negative samples. The essence of this loss function lies in the fact that for each sample x_i, this paper normalizes its similarity score with the positive sample y_i by dividing it by the sum of the similarity scores between x_i and all the samples. This process yields a probability distribution, and the logarithm of this distribution is incorporated into the loss function, which is then averaged across all sample results. The objective of this loss function is to maximize the similarity of positive samples while minimizing the similarity with negative samples, aiming to learn a comprehensive feature representation.

In the global alignment comparison learning of video and text, the objective is to maximize the similarity of correctly paired video-text pairs and minimize the similarity of those that cannot be paired. Subsequently, the video and text representations $\overline{v_i}$ and $\overline{t_j}$ outlined, the contrast loss is computed as expressed in Eq. (4):

$$L_1 = -\sum_{i=1}^{N} log \frac{exp(\, s(\overline{\mathbf{v}}_i , \overline{\mathbf{t}}_i \,) / \tau \,)}{\sum_{j=1}^{N} exp((\overline{\mathbf{v}}_i , \overline{\mathbf{t}}_j \,) / \tau \,)} \tag{4}$$

In the context of finer-grained alignment, comparative learning is still employed to maximize the similarity between correctly paired nouns (pairs of nouns) and, conversely, minimize the similarity between nouns that cannot be correctly paired. The model aims to maximize the similarity between x_n and y_n while minimizing the similarity between x_n and y_n. Here, x_n represents the representation of nouns captured from the video space, y_n represents the representation of correctly extracted nouns from the text, and y_k represents the representation of the sequence of other nouns extracted from the same batch of text.

This approach trains the multimodal encoder by relying on the video sequence representations to identify correctly paired nouns, compelling the video encoder to precisely capture the spatial content. The representation of the loss function is shown in Eq. (5):

$$L_2 = -\sum_{i=1}^{N} log \frac{exp(\, s(x_n^i , y_n^i \,) / \tau \,)}{\sum_{j=1}^{N} exp((x_n^i , y_k^j \,) / \tau \,)} \tag{5}$$

where, x_n^i and y_n^i denote the ith paired sample (positive sample), y_k^j denotes the negative sample of the ith sample, and N denotes the batch size.

Similarly, comparative learning for paired verbs focuses on maximizing the similarity between the verb representation x_v in the video space and the verb representation y_v in the text space. Simultaneously, it aims to minimize the similarity between x_v and other verb representations y_v in the text space. The loss function is expressed in Eq. (6):

$$L_3 = -\sum_{i=1}^{N} log \frac{exp(\, s(x_v^i , y_v^i \,) / \tau \,)}{\sum_{i=1}^{N} exp(\, s(x_v^i , y_p^j \,) / \tau \,)} \tag{6}$$

where, x_v^i and y_v^i denote the ith paired sample and y_p^i denotes the jth negative sample of the ith sample.

E. Objective function

This model finds the optimal model parameters by minimizing the sum of the three losses in Section Ⅲ. *D*. The objective function is as in Eq. (7).

$$L = L_1 + L_2 + L_3 \tag{7}$$

F. Pre-training dataset

The video datasets employed for training this model are MSR-VTT [22] and MSVD [23], both comprising approximately 10K video data. To enhance the model's generalization, pre-training is conducted on the combined dataset of CC-3M [24] and WebVid-2M [1], resulting in approximately 5.5M video-text pairs after the merger.

IV. Experimental Setup

In this study, our experiments aim to investigate whether the dual video-text alignment model enhances video retrieval accuracy. Specifically, the model is anticipated to achieve improved accuracy by incorporating a more nuanced understanding of both the video and description text, in contrast to the prevalent utilization of global features. Ablation experiments are then conducted to discern whether the enhanced retrieval accuracy is attributed to the finer-grained comprehension of the video and description text.

In this section, we initially present the general information and implementation details of the dataset used in the experiment. The model's performance is evaluated by reporting R@K and MdR, and the efficacy of our method is established through comparisons with other video retrieval approaches. We also detail the process and results of the ablation experiments. Additionally, this paper utilizes Grad-CAM [25] for generating class activation maps showcasing model cross-modal attention, and concludes with a case study illustrating the retrieval results of the model.

A. Datasets and Evaluation Metrics

1) Datasets: To benchmark against advanced baseline models and assess the performance of our proposed model, we conducted experiments on two widely used public datasets. The details of the dataset sources and divisions are outlined below:

MSR-VTT is curated with 257 popular queries from a commercial video search engine, encompassing a diverse array of categories and video content. It comprises 10k video clips and 200k descriptions. In previous work [26], the training set consists of 9k clip-text pairs, with the remaining 1k pairs designated for evaluation. This model follows the same division for training and evaluation.

MSVD is selected from YouTube, where each video description is independent and not influenced by the vocabulary or word order choices in previous descriptions. The dataset comprises 1,970 videos, ranging in length from 1 to 62 seconds. Each video is associated with approximately 40 descriptions. The training, validation, and test sets consist of 1200, 100, and 670 videos, respectively. This model undergoes training and evaluation using this standardized partition.

2) Evaluation metrics: To assess the performance of the model proposed in this paper, we employ standard evaluation metrics for video retrieval tasks: K recall (R@K, with K values of 1, 5, and 10, higher being preferable) and median rank (MdR, lower being preferable). R@K calculates the percentage of test samples with correct results within the top-K retrieval points relative to the query samples. Calculated as in Eq. (8):

$$R@K = \frac{TP}{TP+FN} \tag{8}$$

where, TP (True Positives) denotes the number of relevant videos that were correctly retrieved in the first K retrieval results and FN (False Negatives) denotes the number of relevant videos that were not retrieved in the first K results.

MdR measures the median position of the correct option in the sequence, assessing the model's capability to rank relevant videos effectively in the retrieval task.

B. Experimental Details

To facilitate training, the video size is initially adjusted to serve as the original input. Frames are sampled from a video during training, where the size of each patch is set to 16×16. Consequently, each video frame corresponds to one patch with sequence dimensions. The temporal and spatial attention blocks in the TimeSformer are initialized using ViT [8] weights pretrained on ImageNet-21k. The text encoder employs the Transformer architecture with eight attention heads, and the dimension of the common feature space is set to 256. During the training phase, this model utilizes the AdamW [28] optimizer with a learning rate set to 3×10^{-5} and 10 training epochs. Multi-interval learning rate tuning is applied: [4, 8], and weights are decayed to 0.1 times their original values.

Building upon previous research, pre-training using image-text pairs proves effective in enhancing the model's representation of the video space. The images in CC-3M were replicated and transformed into static videos. Additionally, we opted for the WebVid-2M video dataset, featuring 2.5M videos, for joint pre-training alongside CC-3M. This was accomplished using the AdamW optimizer, where the learning rate was set to 1×10^{-4}, the number of epochs was 20, and multi-interval learning rate tuning was applied [12, 16]. The weights were attenuated by a factor of 0.1 times their original values.

V. Results and Discussion

To assess the impact of the video-text dual alignment model proposed in this paper on video retrieval accuracy, Tables I and II in this section present experimental results comparing this method with others on the MSR-VTT and MSVD datasets, with optimal results highlighted in bold. Through a comparison of evaluation metrics such as R@K and MdR, our method exhibits improvements in video retrieval task metrics over comparative models like X-CLIP and DCR.

A. Experimental Results

As depicted in Tables I and II, for the MSR-VTT and MSVD datasets, our method achieves a 1.3 percentage point increase in R@1 compared to previous state-of-the-art approaches. Notably, on the MSVD dataset, the improvement in R@1 is 2 percentage points. Simultaneously, there is a reduction in the MdR value in this task. This demonstrates that the incorporation of finer-grained alignment positively influences retrieval performance, underscoring the effectiveness of the proposed method.

The proposed method employs fine-grained alignment of words in text descriptions with actions or scenes in the video, leading to a more accurate alignment between video and text and improved modeling compared to the X-CLIP model, which outperformed other comparison models. While the ALPRO model introduces the concept of PEM for learning fine-grained region-entity alignment, the fine-grained alignment in our method is notably more pronounced for the retrieval task. Moreover, the Clover model also incorporates the idea of modal alignment to enhance cross-modal feature alignment and fusion. In contrast, our approach utilizes the simpler dual alignment to achieve superior performance while successfully meeting the objective of improving retrieval accuracy outlined in this paper.

TABLE I. COMPARISON RESULTS WITH MAINSTREAM METHODS ON MSR-VTT DATASET

Methods	R@1/%	R@5/%	R@10/%	MdR
Frozen[1]	31.0	59.5	70.5	3.0
ALPRO[27]	33.9	60.7	73.2	3.0
Clover[29]	40.5	69.8	79.4	2.0
MELTR[33]	41.3	73.5	82.5	-
CLIP4Clip[30]	44.5	71.4	81.6	2.0
X-Pool[31]	46.9	72.8	82.2	2.0
X-CLIP[32]	49.3	75.8	84.8	2.0
TEFAL[36]	49.9	76.2	84.4	2.0
DCR[34]	50.2	76.6	84.7	**1.0**
Ours	**51.5**	**78.6**	**86.3**	2.0

TABLE II. COMPARISON RESULTS WITH MAINSTREAM METHODS ON MSVD DATASET

Methods	R@1/%	R@5/%	R@10/%	MdR
SupportSet[35]	28.4	60.0	72.9	4.0
Frozen[1]	33.7	64.7	76.3	3.0
CLIP4Clip[30]	46.2	76.1	84.6	2.0
DiffusionRet[37]	46.6	75.9	84.1	2.0
DMAE[38]	46.9	76.8	85.6	2.0
X-Pool[31]	47.2	77.4	86.0	2.0
DCR[34]	50.0	81.5	89.5	2.0
X-CLIP[32]	50.4	80.6	-	-
Ours	**52.4**	**83.3**	**90.5**	**1.0**

B. Ablation Study

To assess the efficacy of the dual alignment module and evaluate the impact of various comparison modules on retrieval outcomes, ablation experiments were conducted on two datasets, MSR-VTT and MSVD. Results from the ablation experiments are presented in Tables III and IV, while Fig. 3 provides a visual depiction for a more intuitive understanding of the effects of different alignment modules.

Initially, when solely engaged in the global video-text alignment task L_1, the efficiency of video retrieval across all combinations remains relatively low. This suggests a noticeable semantic gap between the global features of video and text modalities. Subsequently, with the inclusion of fine-grained noun alignment or verb alignment tasks ($L_1 + L_2$ or $L_1 + L_3$), the R@1 values on the MSR-VTT dataset improved by 2.8 and 4.2 percentage points, respectively. This indicates that the combination of global alignment and fine-grained alignment contributes to performance enhancement, albeit not significantly.

TABLE III. ABLATION EXPERIMENT ON MSR-VTT UNIT：%

Method	R@1	R@5	R@10
L_1	40.6	67.4	80.5
L_1+L_2	43.4	72.5	84.9
L_1+L_3	44.8	73.1	83.4
L_1+L_2+L_3	**51.5**	**78.6**	**86.3**

TABLE IV. ABLATION EXPERIMENT ON MSVD UNIT：%

Method	R@1	R@5	R@10
L_1	43.6	69.2	83.6
L_1+L_2	46.5	74.8	85.3
L_1+L_3	45.2	73.5	84.9
L_1+L_2+L_3	**52.4**	**83.3**	**90.5**

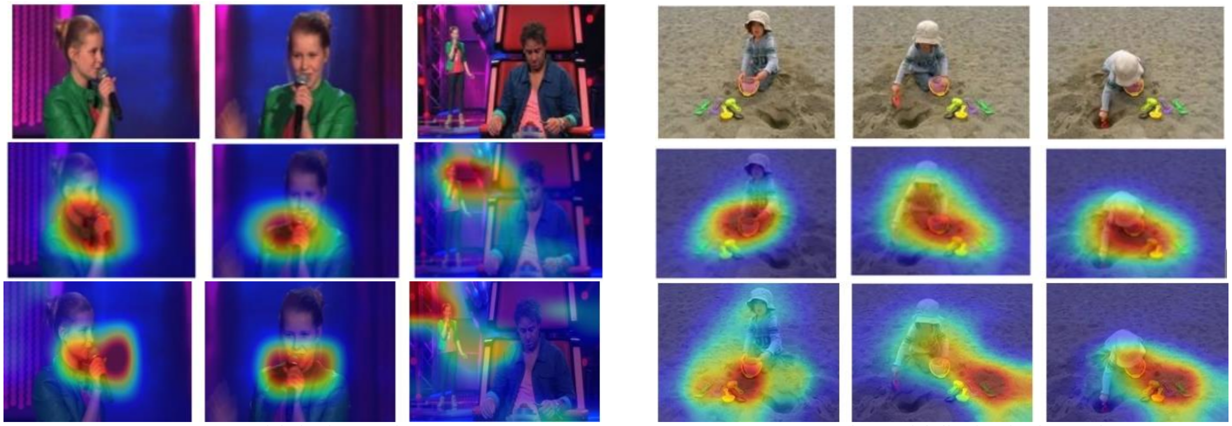
Ultimately, when integrating all three alignment tasks $L_1 + L_2 + L_3$, the model achieves optimal results on both datasets, as depicted in Fig. 3. The R@K values consistently rank highest when utilizing the three alignment strategies, reaching 51.5% and 52.4% at R@1 for the respective datasets. This underscores the effectiveness of combining three alignment strategies in improving retrieval efficiency. Attention Visualization

In the section on fine-grained video-text alignment, this model achieves a comprehensive understanding of the video content. Utilizing Grad-CAM, we generate class activation maps on the MSR-VTT dataset to visually represent the cross-modal attention between the video description and the video. This visualization aids in pinpointing corresponding regions in the video for the nouns or verbs mentioned in the text, showcasing the model's proficiency in fine-grained video-text alignment.

In this study, we employ Grad-CAM to visualize the third layer of the multimodal encoder. To enhance the presentation's clarity, we extract three frames from the video to illustrate the cross-modal attention between the verbs in the text and the video actions. We compare these results with the visualization outcomes of the X-CLIP model. In Fig. 3(a), depicting a scene where a girl sings on stage, our model's visualization captures the continuous focus on the girl's hand and face area, indicating alignment with the word "sing" in the text. Conversely, the X-CLIP model deviates from the girl's hand and face actions, favoring objects behind the girl. In Fig. 3(b), our model's visualization emphasizes the girl's hand movements corresponding to the word "digging" in the text, while the X-CLIP model seems more focused on objects beside the girl than her movements. This suggests that our model exhibits fine-grained cross-modal alignment capabilities compared to other models, emphasizing the importance of such alignment for improving retrieval results.

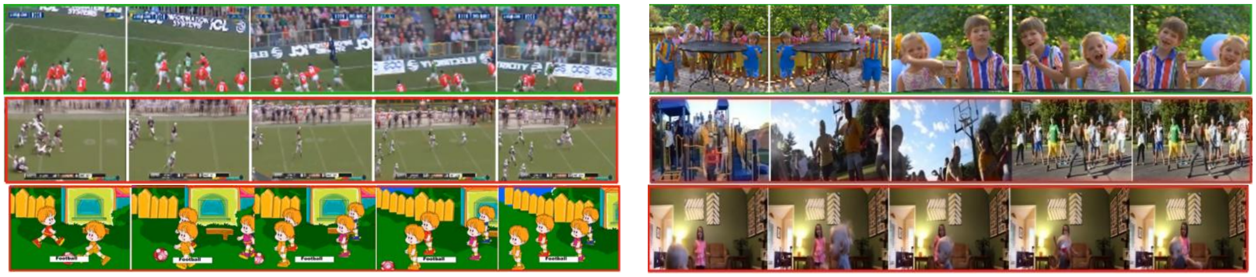
C. Video Retrieval Case

To demonstrate the retrieval effectiveness of the model, we visualize three examples of text retrieval on the test set of the MSR-VTT dataset, as shown in Fig. 4. In example (a), when searching for "two teams playing football," the model successfully retrieves scenes of people playing football, meeting the retrieval criteria. However, only one result is highlighted with a green box, as the model assumes one query corresponds to the optimal result. In Fig. 4(b), searching for "kids are singing by a table" yields the correct result in the first position. While other retrieval results are similar to the optimal one, they do not align with the scene described in the query. This highlights the model's ability to achieve fine-grained alignment between actions and scenes in the retrieval queries and video content, consequently enhancing retrieval efficiency.



(a) “a girl singing on the stage” (b) “a girl digging in the sand”

Fig. 3. Grad-CAM visualizes multimodal encoder cross-modal.



(a) Query: two teams playing football (b) Query: kids are singing by a table

Fig. 4. Text-video retrieval results example.

VI. Conclusion

This paper introduces an efficient video retrieval model through video-text alignment. The model uses TimeSformer and DistilBERT to extract unimodal feature representations from video and text, and performs global video-text alignment by linear projection and contrast learning. Subsequently, the local video information is compared and learned from the textual content by masking part of the textual information in order to achieve fine-grained video-text alignment. By enhancing the cross-modal training process and combining global and fine-grained alignment tasks, the model strengthens semantic associations between modal information, leading to improved alignment and enhanced video retrieval recall. Experiments on MSR-VTT and MSVD datasets validate the model's superiority and method effectiveness.

However, this method also has the non-negligible limitation that it takes a lot of time to perform video-text alignment, and it is also important to find a more efficient alignment.

In future work, we aim to delve deeper into exploring and integrating various modalities in videos, such as audio and subtitles, to further narrow the semantic gap between video and text and enhance the accuracy of video retrieval. Additionally, for the task of video retrieval, there is potential to train models tailored for retrieving videos in specific domains, making the models more specialized and efficient.

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Elevating Neuro-Linguistic Decoding: Deepening Neural-Device Interaction with RNN-GRU for Non-Invasive Language Decoding

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Abstract*—Exploring innovative pathways for non-invasive neural communication with language interfaces, this research delves into the interdisciplinary realm of neurolinguistic learning, merging neuroscience and machine learning. It scrutinizes the intricacies of decoding neural patterns associated with language comprehension. Leveraging advanced neural network architectures, specifically Deep Recurrent Neural Networks (RNN) and Gated Recurrent Units (GRU), the study aims to amplify the landscape of neuro-device interaction. The focus of Neurolinguistic Learning lies in extracting language-related brain signals without resorting to invasive procedures. Employing cutting-edge non-invasive methods and deep learning techniques, the research aims to elevate the capabilities of neural devices such as brain-machine interfaces and neuroprosthetics. A distinctive approach involves crafting a sophisticated Deep RNN-GRU model designed to capture intricate brain patterns linked to language processing. This architectural innovation, implemented in the Python software environment, harnesses the strengths of RNNs and GRUs to enhance language decoding. The study's outcomes hold promise for advancing non-invasive brain language decoding systems, contributing to the expanding knowledge base in neurolinguistic learning. The remarkable accuracy of the proposed RNN-GRU model, boasting a 90% accuracy rate, signifies its potential application in critical real-world scenarios. This includes assistive technologies and brain-machine interfaces where precise decoding of cerebral language signals is paramount. The research underscores the efficacy of deep learning methodologies in pushing the boundaries of neurotechnology. Notably, the model outperforms established techniques, surpassing alternatives like CSP-SVM and EEGNet by an impressive 30.4% in accuracy. The model's proficiency in deciphering topic words underscores its ability to extract intricate language patterns from non-invasive brain inputs.

Keywords*—Recurrent Neural Networks (RNN); Gated Recurrent Units (GRU); neurolinguistic learning; neural devices; brain machine interfaces

I. INTRODUCTION

Within the quickly developing field of neurotechnology, the goal of creating a seamless interface between the human brain and external devices has spurred innovative research efforts [1]. Neuro technology is advancing by developing neural-device interaction, an interdisciplinary field that combines neuroscience and engineering to improve two-way communication between neural systems and external devices, aiming to create a seamless interface [2]. Addressing fundamental issues and opening up new avenues for human-machine interfaces are the driving forces behind the advancement of neural-device interaction [3]. Conventional means of communication between neural devices and the brain frequently struggle with issues of signal integrity, bandwidth of information, and procedure invasiveness [4]. It is becoming increasingly important to overcome these obstacles as technology develops in order to improve our comprehension of neural processes and to use this knowledge for useful applications that help people with neurological disorders, disabilities, or those looking to enhance their cognitive abilities.

The understanding of neural signaling’ s complexity and the need for advanced models capable of real-time signal interpretation and deciphering are at the core of this research endeavor [5]. One promising approach is the use of deep reinforcement learning networks (DNRNNs) and GRUs. The dynamic information embedded in neural signals linked to different cognitive functions can be decoded by these models, which are excellent at capturing temporal dependencies and sequential patterns [6]. Learning more about neural-device interaction is important not only for academics and researchers, but also for a wide range of applications in human-computer interaction, rehabilitation, and healthcare [7]. More innovative assistive technologies, tailored therapeutic interventions, and more successful neuroprosthetics can all be made possible by improved neural-device interfaces [8].

Furthermore, these developments pave the way for revolutionary discoveries in areas like brain-machine interfaces, neuromodulation, and cognitive augmentation by facilitating a more intuitive and natural interaction between people and machines [9]. This research explores various methods for data collection and neural network architecture creation, emphasizing non-invasiveness. It describes a workflow for deep RNN-GRU-based neurolinguistic learning to improve neural-device interaction. The goal is to advance brain functions and foster a new era of human-machine cooperation [10].

A growing field identified as neurolinguistic learning has emerged from the dynamic intersection of neuroscience and artificial intelligence in an effort to understand the neural basis of language [11]. In an effort to uncover the mysteries buried in the neural code that underpins our capacity for language comprehension and production, this research explores the complex relationship between neural activity and language processing. Neurolinguistic learning aims to directly access the neural substrate of language, in contrast to traditional linguistic analyses, which rely on external behavioral measures. This approach provides a more nuanced and direct understanding of the cognitive processes involved. The realization that language, a distinguishing feature of human cognition, is not limited to observable behaviors or linguistic outputs is what spurred researchers to explore the field of neurolinguistic learning [12]. Rather, it is firmly anchored in the intricate and dynamic neural activity patterns that emerge inside the brain.

Specifically, non-invasive neural language decoding is the emphasis of this research, which is an important application of neurolinguistic learning [13]. Using invasive techniques like brain electrode implantation, the traditional methods for deciphering neural language patterns are frequently applied. Concerns about safety, ethics, and the need to create more widely available technologies, however, drive the search for non-invasive alternatives. Understanding neural language processes can be gained without invasive procedures by using non-invasive techniques like functional magnetic resonance imaging (fMRI) and electroencephalography (EEG). This work aims to apply deep learning models, namely Deep RNN and GRU, to advance the state-of-the-art in non-invasive neural language decoding. These architectures are especially well-suited to modeling the dynamic nature of language processing because they are good at capturing sequential patterns and temporal dependencies. Through the use of these sophisticated neural network architectures, the research hopes to shed light on the complexities of neural language representation and, as a result, improve our comprehension and decoding skills for the ideas encoded in neural language [3].

Non-invasive neural language decoding has potential to revolutionize assistive technology, neurorehabilitation, and communication technology. It can help people with communication impairments, offer new perspectives on cognitive processes, and create more user-friendly interfaces. This project combines linguistics, artificial intelligence, and neuroscience, transforming our understanding of language and the human mind. [14].Improving the smooth connection between neural devices and the complex processes of language expression and comprehension is one of the main issues in this field [1]. The need to overcome the drawbacks of the invasive procedures that are typically used in neural interface development is what drives this research [15]. Even though they work well, invasive techniques like implanting electrodes directly into the brain come with risks, such as tissue damage and infections. As a result, the search for non-invasive substitutes has taken center stage in the development of neural-device interfaces [16]. This project specifically focuses on leveraging advanced neural network architectures, namely Deep RNN and GRU, to decode neural language signals without resorting to invasive interventions.

Our main focus is on the field of neurolinguistic learning, which investigates the complex connection between language processing and brain activity. The complexity of language patterns is a challenge for traditional neural interfaces because of the difficulties in decoding the rich and dynamic information contained in neural signals. In this work, the author explore the potential of deep learning—more especially, RNN-GRU models—to non-invasively decipher the complex patterns related to language. RNN-GRU models were specifically chosen because of their demonstrated ability to handle sequential data and capture temporal dependencies. These architectures offer a sophisticated understanding of how neural signals encode linguistic information over time, making them well-suited to simulate the dynamic nature of language processing. Through these advanced neural network architectures, we hope to open up new possibilities for neural devices and usher in a new era of non-invasive neural language decoding.

The practical applications of this research have transformative potential and go beyond the domain of neuroscience. A successful implementation could transform augmentative communication technologies and make it possible for people with disabilities or communication disorders to express themselves with never-before-seen ease. Furthermore, our method's non-invasiveness reduces related health risks and encourages accessibility and broad acceptance.

The key contributions of the article is,

- The work proposes a non-invasive method for neurolinguistic learning that harvests language-related brain signals without necessitating invasive procedures. This is achieved by utilizing the most advanced deep learning algorithms, specifically Deep RNN-GRU.
- The study increases the possibility of neuro-device interaction by using complex neural network architectures, notably Deep RNN and GRU. This technology has significant promise for non-invasive neuro-communication applications in both ethical and helpful situations. The incorporation of these topologies facilitates the capture of complex brain patterns associated with language processing in the creation of neurotechnological interfaces.
- The real contribution is the development and use of the Deep RNN-GRU model, which is done using the

Python programming language. This well-designed architecture plays to the strengths of RNNs and GRUs while showcasing an advanced tool for improved language decoding, encouraging transparency and reproducibility within the scientific community.

- The work offers novel and analytical techniques for deciphering language-related brain signals, which significantly advances the rapidly expanding field of neurolinguistic learning. The exceptional accuracy and performance of the suggested RNN-GRU model demonstrate its potential as a revolutionary tool in the ongoing advancement of non-invasive neural language decoding systems.

The remainder sections of the article includes related works, problem statement, methodology and results in Sections II, III, IV and V respectively. The paper is concluded in Section VI.

II. Related Works

Dash et al. [17] proposed neural interpretation of speech in amyotrophic lateral sclerosis. A motor neuron-related illness identified as ALS can result in locked-in syndrome, which is total paralysis with awareness. Through brain computer interfaces, such as EEG spellers, which have a low communication rate, these locked-in patients can converse. Neural speech decoding paradigms that could lead to normal communication rates have been the focus of recent research. However, the focus of current neural decoding research is on typical speakers, and it is unclear how far these findings can be applied to a target population (such as those with ALS). The study examined the decoding of spoken and imagined phrases from non-invasive magnetic resonance imaging signals of individuals with ALS using seven machine learning decoders and multiple spectral characteristics (band-power of neural signals: delta, theta, alpha, beta, and gamma frequency ranges). The outcomes of the experiment showed that while ALS patients' decoding performance is considerably higher than chance, it is still lower than that of healthy individuals. For five imagined phrases and five spoken phrases from ALS patients, the best scores were 75% and 88%, respectively. As far, this is the first instance of neural speech decoding for a population with speech disorders. The disadvantage is that in order to confirm the study's effectiveness, analysis involving a greater number of individuals with more severe ALS and multiple sessions are required. Moreover, improved neurolinguistic comprehension of the imagining of speech would facilitate the development of algorithms for improved imagined speech decoding performance.

Cooney et al. [13] proposed an EEG-fNIRS bimodal deep machine learning design for overt and imagining speech decoding. Research on brain-computer interfaces is increasingly utilizing various characteristics of multiple signal modalities at the same time. The bimodal gathering procedures that integrate the temporal and spatial resolutions of electroencephalography and near-infrared spectroscopy require new decoding techniques. Present an EEG-fNIRS hybrid BCI that utilizes a unique bimodal in nature deep neural network design consisting of two convolutional sub-networks to decode both overt and imagined speech. Each subnet's features are fused before being further extracted and categorized. Classification accuracy using the hybrid approach showed substantial gains on EEG used independently for imagined speech ($p = 0.02$) and a tendency towards a significance for overt speech .The classification accuracy was 46.31% and 34.29%. Bimodal decoding produced significantly better results for both speech types when compared to fNIRS .While stimulus affected overt and imagined words in significantly different ways, deeper subnets improved performance. The bimodal approach performed significantly better than the unimodal results for several tasks. The results imply that neural signal decoding could be enhanced by multi-modal deep learning. With this novel architecture, speech deciphering from bimodal in nature neural signals can be enhanced.

Llanos et al. [18] proposed peripheral stimulation of nerves without invasive procedures improves speech in adults category learning. In animal models, vagus nerve stimulation has been demonstrated to prime adult sensory-perceptual systems towards plasticity. Accurate temporal integrating with auditory stimuli can significantly improve the specificity of auditory cortical representations. Here, the study investigated whether adult speech category learning is improved by sub-perceptual thresholds transcutaneous stimulation of the vagus nerve in conjunction with non-native speech sounds. To recognize non-native Mandarin tone categories, twenty-four native English speakers received training. The tVNS was matched with the tone groups that were either easier or harder to learn for each of the two groups. While receiving no stimulation, the control group used the same thresholding process as the intervention groups. Our findings showed that tVNS significantly improved learning and retention of accurate stimulus-response associations for speech categories, but only when stimulus was combined with categories that were simpler to learn. This effect manifested quickly, generalizing to new exemplars, and differed qualitatively from the typical individual variability seen in hundreds of learners completing the same task in the absence of stimulus. Before and after training, electroencephalography recordings showed no signs of tVNS-induced modifications to the sensation representations of auditory stimuli. According to these findings, paired-tVNS selectively improves both perception and consolidation of memories of intuitively salient categories by inducing a temporally exact neuromodulatory signal.

Feng et al. [19] proposed brain and language semantic alignment: a curriculum contrastive approach for electroencephalography-to-text generation. The tremendous potential for brain-computer interfaces has led to a growing interest in Electroencephalography-to-Text creation, which attempts to produce natural text from EEG signals. But a significant obstacle to this task is the striking difference between the semantic-dependent representation of text and the subject-dependent EEG representation. In order to address this, the study develops a Curriculum Semantic-aware Contrastive Learning approach that reduces the discrepancy by effectively recalibrating the subject-dependent EEG representation to the semantic-dependent equivalent. More precisely, semantically similar EEG representations are pulled together by our C-SCL, while dissimilar ones are pushed apart. Furthermore, carefully utilize curriculum learning to both craft and make the learning progressively meaningful contrastive pairs in order to incorporate more meaningful contrastive pairs. Numerous experiments on the ZuCo benchmark, and our approach, when combined with various models and architectures, achieve the new state-of-the-art while demonstrating steady improvements through three types of metrics. Additional research demonstrates not just its advantages in low-resource and single-subject settings, but also its strong generalizability in zero-shot scenarios.

Lee et al. [20] proposed deciphering language-specific imagined speech neural correlation through EEG signals. Degenerative diseases and brain lesions can cause devastating speech impairments. For people with severe speech deficits, the use of imaginary speech in brain-computer interfaces has proven to be an urging hope for reestablishing speech production nerve impulses. However, due to low signal-to-noise ratio and high variation in both temporal and spatial information, studies in the EEG-based simulated speech domain still have some limitations. In this work, the author examined the neural signals of two native speaker groups performing two tasks in separate languages like English and Chinese. The study postulated that the tonal and ideogram-based Chinese language and the non-tonal and phonogram-based English language would differ spectrally in how their brains computed speech. The results showed that, in some frequency band groups, Chinese and English had significantly different corresponding power spectral densities. Furthermore, native Chinese speakers in the theta band demonstrated distinct spatial evaluation during the imagination task. In order to decode the brainwaves of speech, this paper will therefore propose the essential the spectral and spatial data of word creativity with specialized language. The main flaw is that while the experiment's imagination tasks were designed to categorize words using machine learning algorithms, there hasn't yet been any evaluation of the classification performance.

Jensen et al. [21] proposed MVPA analysis of intertribal phase coherence of neuromagnetic responses to words reliably classifies multiple levels of language processing in the brain. One of the least understood aspects of the human brain is language's neural processing, yet a number of circumstances call for an objective, participant-friendly, and noninvasive assessment of the language function's neurocognitive state. A brief task-free recording of MEG reactions to a series of spoken language contrasts was suggested as a basis for a solution to this problem. Spoken stimuli with differences in lexicon, semantics, were used. The multivariate pattern analysis to investigate intertribal phase coherence in five canonical bands based on beam former source reconstruction is utilized. By employing this method, effectively distinguish between the brain responses to real words and pseudo words, between proper and improper syntax, and between semantic variations. The most accurate classification results showed dispersed activity patterns that were augmented by other regions while being dominated by the core temporofrontal language circuits. The neurolinguistic properties varied across frequency bands; broad γ was used to classify lexical processes, α and β was used to classify semantic distinctions, and low γ feature patterns were used to classify syntax. Importantly, every kind of processing started almost simultaneously 100 milliseconds after the auditory data made it possible to distinguish between spoken and written input. This demonstrates that distinct neuronal networks operating at different frequency bands are involved in individual neurolinguistic processes, which occur simultaneously. This gives rise to even greater hope that neurolinguistic processes in a variety of populations can be objectively and noninvasively evaluated using brain imaging. The disadvantage is that in order to determine whether this method can be used to identify linguistic abnormalities in different populations, it is necessary to fully comprehend the relationship between time courses, frequency bands, neuronal substrates, and neurolinguistic properties.

Time courses, frequency bands, neuronal substrates, and neurolinguistic properties interact in a way that necessitates a thorough comprehension of the approach being considered for detecting linguistic abnormalities in different populations. Although this has great potential, a major limitation is that the classification performance of the word categorization tasks created with machine learning algorithms is not evaluated. Nevertheless, more recent studies demonstrate the method's strong generalizability in zero-shot scenarios in addition to its benefits in low-resource and single-subject settings. Notably, despite subnets not being specifically designed for different data types and suboptimal fNIRS data timing, the dual network enhancement in the majority of subjects' results is a promising result. However, for wider application, resolving the method's drawbacks and carrying out a comprehensive assessment of its overall performance are still essential.

III. Problem Statement

Despite considerable progress in the development of neural-device interfaces, the seamless and efficient communication between the human brain and external technologies remains a formidable challenge. The limitations of current approaches, particularly the invasive nature of many brain interfaces, pose significant risks and hinder widespread adoption. This study addresses this pressing issue by proposing an advanced methodology employing Deep Recurrent Neural Networks (RNN) and Gated Recurrent Units (GRU) for neurolinguistic learning, aiming to provide non-invasive alternatives. The primary objective is to decode cerebral language signals in a non-intrusive manner, representing a crucial initial step towards enhancing the safety and usability of neural interfaces in applications such as assistive technologies, neuroprosthetics, and brain-machine communication. The existing landscape of non-invasive neural language decoding struggles to capture the intricate sequential patterns inherent in language processing. The complexity and dynamism of language-related brain signals pose challenges for conventional techniques. Consequently, the research advocates for the integration of deep RNN-GRU architectures, renowned for their proficiency in capturing sequential dependencies, into the neurolinguistic learning framework. The central challenge lies in designing and optimizing deep learning models to advance our understanding of non-invasive neural language decoding, thereby facilitating more effective and user-friendly neuro-device interactions [21].

IV. Proposed Deep RNN-GRU based Neurolinguistic Learning

The methodology advances non-invasive communication between brain devices and language interfaces by utilizing a multidisciplinary approach based in neurolinguistic learning. The study explores the complexities of deciphering language-related brain patterns, with a focus on the interface between neuroscience and machine learning. By utilizing cutting-edge neural network topologies, particularly Deep RNN and GRU, the study seeks to improve the capabilities of neuro-device interaction. Because the process is non-invasive, there is no need for intrusive procedures, which ensures both practical and ethical viability. A Deep RNN-GRU model is painstakingly built in Python to capture intricate brain patterns related to language processing. The model's ability to decipher complex language patterns, particularly for subject words, indicates its potential for practical uses such as brain-machine interfaces and assistive technologies. This represents a major advancement in the integration of neurolinguistic learning and neurotechnology. The proposed methodology is shown in Fig. 1.

A. Data Collection

Eleven healthy volunteers within the ages of 20 and 34 were recruited for this study, six of them were male and five of them were female. Respondents were made aware of the methods, frameworks, and goals before to the study. Every participant provided written permission in accordance with the Declaration of Helsinki, and all research methods were approved by Korea University's Institutional Review Board. Eight terms that represent the subject, verb, and object parts of the sentence were selected for the experimental setting based on their applicability to natural human-machine interaction, particularly with neural mechanical arm control. The fundamental language was made up of these words, which included subjects like "I" and "partner," verbs like "move," "have," and "drink," and object terms like "box," "cup," and "phone." Every phrase was said by those taking part 25 times, and their audio cues were captured. Respondents wore 64-channel EEG actiCaps during the EEG monitoring session, and MATLAB 2020a software's BrainVision Recorder was used to record EEG signals. Respondents in the study completed speech imaging tasks for every single one of the three sub sessions that focused on subject, verb, and object terms, correspondingly. High signal quality was maintained during the entire trial by providing students with pauses to preserve their physical and mental health and by displaying illustrations on a monitor [22].

One method for transforming EEG signals into a format that is easier to analyze and understand is called spectrogram embedding. EEG data, which show the brain's electrical activity over time, are frequently intricate and provide important insights into cognitive functions. By converting the EEG signal into a spectrogram—a graphic depiction of the signal's frequency content across time spectrogram embedding is achieved. The first step in the procedure is to divide the EEG signal into smaller temporal chunks, or epochs. By doing this, the EEG signal is converted from the time domain to the frequency domain, displaying the various frequency components that are present. Following that, the data is usually shown as a two-dimensional picture with time on one axis and frequency on the other. The shading or color intensity of the image indicates the amplitude of each frequency at a certain moment in time.

B. Preprocessing using Bandpass Filter

The role of a Bandpass Filter is paramount in signal processing, serving to selectively permit a specified range of frequencies while attenuating frequencies outside this designated band. This filter is instrumental in various applications where isolating specific frequency components from a signal is crucial. In fields such as telecommunications, audio processing, and biomedical signal analysis, Bandpass Filters help extract relevant information by allowing only the desired frequency range to pass through. In the context of communication systems, Bandpass Filters aid in frequency division multiplexing, enabling multiple signals to coexist without interference. Moreover, in biomedical applications, Bandpass Filters are essential for isolating physiological signals of interest, such as detecting heartbeats in an ECG. Their versatility in isolating and enhancing specific frequency components makes Bandpass Filters indispensable tools in signal processing, facilitating accurate and targeted analysis across diverse domains.

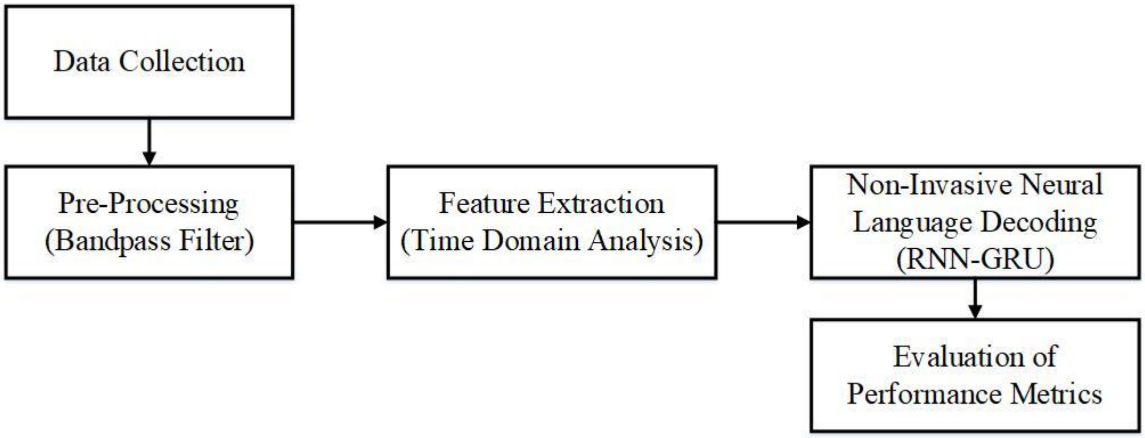
Data Collection
Pre-Processing (Bandpass Filter)
Feature Extraction (Time Domain Analysis)
Non-Invasive Neural Language Decoding (RNN-GRU)
Evaluation of Performance Metrics

Fig. 1. Proposed methodology.

Applying a Bandpass filter to EEG signals during preprocessing is a crucial step in improving the specificity and quality of brain information derived from the raw data. By selectively allowing some frequencies and attenuating others, the bandpass filter helps to separate the brain oscillations of interest from possible noise and artefacts. One common option for EEG data linked to language activities is to apply a bandpass filter in a certain frequency range, this range has been deliberately selected to include the brain frequencies associated with cognitive functions such as language comprehension and speaking. Unwanted elements, including muscular artefacts or outside interference, are reduced by using the bandpass filter, which makes it possible to analyze the brain activity related to the experimental task more narrowly. Bandpass filtering is important for EEG preprocessing because it can increase the signal-to-noise ratio, which guarantees that the underlying brain signals are more accurately represented in the studies that follow. This specific stage is critical for reliably extracting features for applications requiring nuanced brain patterns, such as language decoding. By helping to improve the overall quality of the EEG data, bandpass filtering advances our knowledge of the brain mechanisms underlying language and communication by enabling more precise interpretations and insights into the neural dynamics linked to cognitive activities.

C. Feature Extraction using Time Domain Analysis

Feature Extraction using Time Domain Analysis serves a crucial role in the neuro-linguistic decoding framework presented in this article. It involves the identification and extraction of relevant features from temporal data patterns associated with neural language signals. By delving into the time domain, this technique enables the model to capture subtle variations and temporal nuances inherent in the non-invasive brain signals. This process enhances the discriminative power of the features fed into the subsequent RNN-GRU model, contributing to the accurate decoding of complex linguistic patterns. Essentially, Feature Extraction using Time Domain Analysis acts as a critical pre-processing step, facilitating the comprehensive representation of temporal information and thereby augmenting the overall effectiveness of the neuro-linguistic decoding system proposed in the study.

Time-domain analysis feature extraction turns out to be a crucial step in deciphering the temporal complexities of EEG signals related to language processing, which is important in the quest to advance neural-device interaction through deep RNN-GRU based neurolinguistic learning for non-invasive neural language decoding. Time-domain features provide a way to describe the dynamic interaction between language components and brain activity throughout the experimental tasks. These features are produced directly from the timing and amplitude information of EEG data. An important temporal aspect of this research is the examination of Event-Related Potentials (ERPs). ERPs are the mean brain responses that are time-locked to certain events, such words being presented in speech-imaging tasks. Researchers can learn more about how the brain responds to language inputs over time by extracting ERPs. The characteristics of ERP components, such as their peak amplitudes, latencies, and durations, offer a thorough description of the brain dynamics connected to various language components. The Mean Absolute Value (MAV) is given below,

$$\text{MAV} = \frac{1}{M}\sum_{j=1}^{M}|y_j| \tag{1}$$

The length of the sample is denoted by M.

When analyzing EEG data, zero crossing is an essential time-domain feature extraction technique, especially when trying to comprehend the temporal dynamics of brain activity. Finding the locations in the EEG signal where the amplitude crosses the zero axis is the goal of this approach. Zero crossing analysis offers important insights into the frequency and pattern of oscillatory variations in the EEG signal, providing information about the underlying brain processes connected to language-related activities in the context of neurolinguistic learning. Researchers can extract features that describe the frequency of transitions between positive and negative voltage values by measuring the number of times the EEG waveform crosses zero within a certain time interval. This characteristic is particularly relevant for identifying rhythmic neural patterns and can enhance the effectiveness of non-invasive neural language decoding techniques by providing a thorough grasp of the temporal dynamics of brain activity during language processing tasks.

$$\{y_j < 0 \text{ and } y_{j+1} > 0\} \text{ or } \{y_j > 0 \text{ and } y_{j+1} < 0\} \tag{2}$$

The consecutive samples are denoted as y_j and y_{j+1}.

To better clarify the timing elements of brain responses during language activities, the study may also concentrate on temporal features including signal length, rise time, and fall time. These behavioral characteristics add to our sophisticated knowledge of the brain's real-time processing of language data. Time-domain analysis is applied to both neural language pattern decoding and deep RNN-GRU model training, where it captures the sequential dependencies present in EEG data related to non-invasive language decoding. This methodological approach is in line with the overall objective of improving neural-device interaction, which will aid in the creation of more efficient and user-friendly brain-machine interfaces for a range of applications in assistive technologies, rehabilitation, and communication.

D. Deep RNN-GRU-based Neurolinguistic Learning for Non-Invasive Neural Language Decoding

RNN-GRU plays an important role in sequential data processing tasks, exhibiting distinct advantages in capturing and understanding temporal dependencies within input sequences. The GRU architecture, a variant of traditional RNNs, introduces gating mechanisms that enable more effective handling of long-range dependencies and mitigate issues like vanishing gradients. This makes RNN-GRU particularly well-suited for applications such as natural language processing, time series analysis, and speech recognition, where contextual information across different time steps is crucial. The inherent ability of RNN-GRU to selectively update and forget information, combined with its parallel processing capabilities, enhances its efficiency in modeling complex temporal patterns. These networks have proven instrumental in tasks requiring nuanced understanding of sequential data, making them a valuable asset in advancing various fields.

The development of deep RNNs and GRUs has led to major breakthroughs in neurolinguistic learning, a cutting-edge discipline at the nexus of neuroscience and linguistics. By non-invasively decoding cerebral language patterns, this novel method seeks to open up new avenues for comprehension of the complex interplay between language processing and brain activity. Deep RNN-GRU models are an advanced type of neural networks that are very useful for language decoding tasks since they are made to collect and analyze temporal connections in sequential input. Because of the GRU's capacity to store and update information selectively across long periods, the design makes it possible to represent language-related brain signals' fluctuations in time in a sophisticated manner.

The ability of deep RNN-GRU models to handle variable-length sequences present in natural language is a significant benefit in neurolinguistic learning. The network can learn hierarchical characteristics of language representation, from intricate syntactic patterns to subtle phonetic variations, thanks to its hierarchical structure. It is ideally suited for deciphering brain signals linked to different language processes because of its versatility. These models are very useful for non-invasive neural language decoding. Conventional approaches frequently entail intrusive techniques like brain electrode implantation, which restricts their application and raises ethical questions. However, non-invasive neuroimaging data, like electroencephalography (EEG), may be used to train deep RNN-GRU models, making this method more generally applicable and morally sound.

During the training phase, the model is exposed to language stimuli while brain activity is being recorded. The deep RNN-GRU continuously improves its capacity to decipher language-related information from brain signals by learning to associate particular patterns in the input data with matching linguistic qualities. The model will get more and more adept at capturing the complex links between brain activity and language representation thanks to this iterative learning process. Deep RNN-GRU-based neurolinguistic learning has a wide range of significant applications. In addition to basic studies on the neurological underpinnings of language, this method has applications in therapeutic situations. It may, for example, aid in the creation of assistive technology for people with communication impairments or function as a tool for tracking alterations in language-related brain activity in response to treatment measures.

Even with the advancements, deep neurolinguistic learning still faces several obstacles. Further work is needed to address ethical issues with permission and privacy, interpretability of learnt representations, and generalization of models across different populations. Interdisciplinary cooperation among neuroscientists, linguists, and machine learning specialists is becoming more and more important as the field develops in order to overcome these obstacles and realize the full potential of deep RNN-GRU-based neurolinguistic learning.

Eq. (3) represents the hidden state update h_t at time t in the RNN. Here, y_t is the input at time h_{t-1} is the hidden state from the previous time step, V^h is the weight matrix associated with the hidden state, and tanh is the hyperbolic tangent activation function. The tanh function introduces non-linearity, allowing the network to capture complex relationships and patterns in the data.

$$h_t = \tanh\,(V^h y_t + V^h h_{t-1}) \tag{3}$$

$$x_t = V^h h_t \tag{4}$$

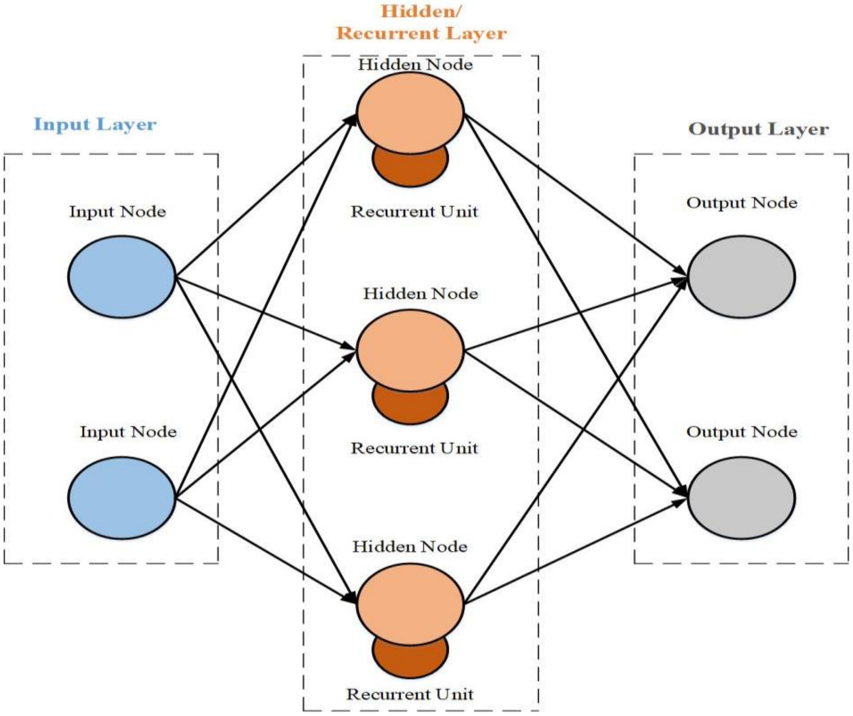

Fig. 2. RNN-GRU architecture.

Fig. 2 shows the architectural diagram of the RNN-GRU model. The above equations form the basis of a GRU, a kind of RNN architecture intended to effectively capture and handle sequential data. The update gate z_t and reset gate r_t, which are both triggered by the sigmoid function σ, are defined by Eq. (3). By deciding what to keep from the prior hidden state h_{t-1} and the current input y_t, these gates control the flow of information. Eq. (4) uses the tanh function to generate the candidate hidden state $\widetilde{h_t}$ and integrates the reset gate r_t to update the hidden state selectively. To provide a seamless transition between the past and current states, Eq. (5) finally combines the update gate z_t with the former hidden state and the candidate hidden state. All together, these formulas describe the complex dynamics of a GRU, which allows it to efficiently recognize and learn sequential patterns in a variety of contexts, including natural language processing and maybe neurolinguistic learning.

$$z_t = \sigma\ (y_t W^z + h_{t-1} V^z) \tag{5}$$

$$r_t = \sigma\ (y_t W^r + h_{t-1} V^r) \tag{6}$$

$$\widetilde{h_t} = \tanh\ (y_t W^h + (r_t * h_{t-1}) V^h) \tag{7}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * h_t \tag{8}$$

RNN-GRU Algorithm

```
Load and preprocess data      // Bandpass filter
Feature Extraction            // Time Domain Analysis
Define RNN-GRU model architecture
    Split data into training and testing sets
Train the RNN-GRU model
Evaluate the model on the test set
Make predictions on new data
Visualize results
```

V. Results and Discussion

With a foundation in neurolinguistic learning, the methodology advances non-invasive communication between language interfaces and brain devices through a multidisciplinary approach. Situated at the nexus of neuroscience and machine learning, the research delves into the complexities involved in deciphering brain patterns linked to language. The goal of the project is to improve neuro-device interface capabilities by utilizing cutting-edge neural network topologies, including Deep RNN and GRU. Because the approach is non-invasive, it ensures both ethical and practical feasibility by removing the need for intrusive operations. A Deep RNN-GRU model that is carefully designed to capture intricate brain patterns related to language processing is created using Python. The model represents a major advancement in the fusion of neurolinguistic learning and neurotechnology because of its ability to decode complex language patterns, particularly for subject words. This shows the model's potential for use in assistive technologies and brain-machine interfaces.

A. Model Loss

The model loss is a key metric of the model's performance during training. It is commonly expressed as a mathematical measure of the dissimilarity between expected and real neural language patterns. When the loss trend is trending downward, the model is doing a good job of reducing mistakes and modifying its parameters to better suit the training set. A steady decline in loss values across epochs indicates that the non-invasive brain signals have been successfully learned to recognize and adjust to. On the other hand, variations or plateaus in the loss trajectory call for further examination and may indicate that the model needs its hyper parameters adjusted or that overfitting or underfitting occurred. Moreover, comprehending the relationship between decoding accuracy and loss offers a thorough grasp of the model's generalization capabilities and clarifies how resilient it is when decoding a variety of neural language patterns. It is depicted in Fig. 3.

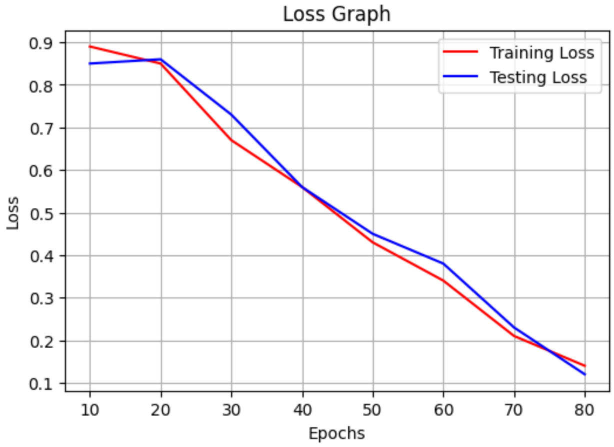

Fig. 3. Model loss.

B. PVC Performance

A statistic called Percent Valid Correct (PVC) performance is employed, especially in cognitive or behavioral studies, to measure the precision and dependability of a classification or prediction system. It shows the proportion of accurate answers or forecasts among all valid cases that were taken into account for a task or experiment. This statistic only looks at how well the system performs when a legitimate answer or forecast can be made; it ignores incorrect or ambiguous data items. This statistic offers a more focused evaluation of the system's effectiveness by highlighting its accomplishments particularly in situations where a significant answer or forecast is anticipated.

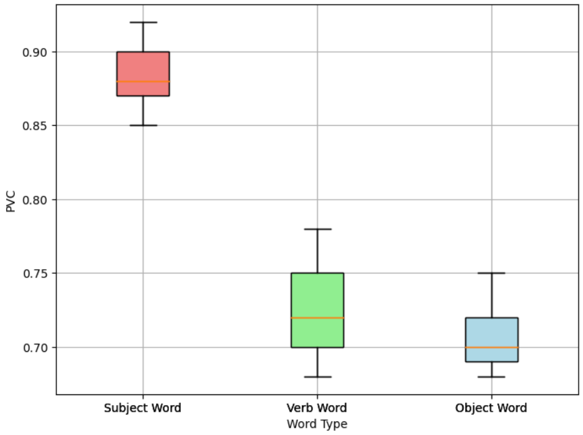

Fig. 4. PVC performance.

A thorough assessment of the model's capacity to decipher brain language patterns is provided by Fig. 4, which shows PVC Performance across many linguistic aspects, namely subject words, verb words, and object words on the x-axis. The way that PVC performance is distributed among various linguistic components provides information on how well the model can identify and anticipate different sentence structure components. Differences in the PVC performance of subject, verb, and object words might be a sign of various brain representations for these linguistic components or of varying degrees of complexity. Understanding the model's complex reactions to many aspects of language requires analyzing the PVC performance across these categories. Doing so may reveal brain activity patterns that alter according to grammatical functions. Furthermore, it offers useful data for adjusting the architecture and training strategies of the model to improve decoding accuracy across various linguistic components, which helps to improve neurolinguistic learning techniques in non-invasive neural language decoding paradigms.

C. Decoding Accuracy over Time

A statistic called decoding accuracy over time is used to evaluate how well a neural decoding model performs and changes over the course of an experiment or activity. This statistic assesses how well the model can predict and understand neural patterns linked to certain cognitive processes or stimuli throughout time. The decoding accuracy's dynamic nature over time offers valuable insights into the model's flexibility and learning dynamics, demonstrating its ability to grasp temporal variations in brain activity. Researchers can identify patterns, trends, or fluctuations in the model's performance by analyzing decoding accuracy at various time intervals. This provides a thorough knowledge of the model's ability to detect and adapt to temporal variations in cognitive or language processing. This measure is especially useful for research using time-series data, such EEG signals, since it offers a detailed assessment of the model's performance in real-time and its possible applications, such as brain-machine interfaces and neurolinguistic learning.

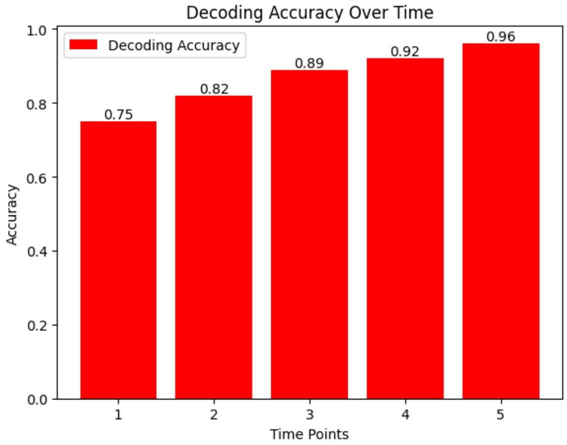

Fig. 5. Decoding accuracy over time.

A more comprehensive illustration of how the model's accuracy changes throughout the course of the task or experiment is given in Fig. 5. Decoding accuracy trajectory tracking over time can show learning, adaptation, or stabilization tendencies in response to changing cognitive demands. Accuracy peaks or troughs at particular times might be related to different stages of the experiment, such when stimuli are presented or when language tasks are performed. Determining the model's sensitivity to temporal changes in brain activity and maybe identifying crucial intervals for optimal performance require an understanding of the oscillations in decoding accuracy. Furthermore, this temporal analysis provides useful insights for improving the model, helping scientists adjust parameters or add adaptive techniques to improve accuracy at critical times. In the end, this helps develop more efficient and temporally-aware neural decoding systems for use in neuroscience and brain-machine interfaces.

D. PVC Distribution across Different Word Types for Various Methods

The pattern or spread of PVC performance across several categories or classes of words within a given dataset is referred to as the PVC distribution across various word kinds. This metric measures the precision of a classification or decoding system and evaluates its performance over a range of linguistic aspects, especially in the context of neurolinguistic learning or non-invasive brain language decoding. The distribution analysis seeks to identify any differences in the model's ability to decode various word kinds, including verb, object, and subject terms. Gaining an understanding of the PVC distribution allows one to assess the model's performance in a more complex way by gaining insight into how sensitive and flexible it is to different linguistic elements.

TABLE I. PVC DISTRIBUTION ACROSS DIFFERENT WORD TYPES FOR VARIOUS METHODS

Methods	Subject Word	Verb Word	Object Word
CSP-SVM [23]	0.60	0.52	0.48
EEGNet [24]	0.78	0.56	0.53
Proposed RNN-GRU	0.90	0.72	0.70

Table I presents the decoding accuracy ratings for the various techniques (CSP-SVM [23], EEGNet [24], and the suggested RNN-GRU model) for various linguistic components (verb, object, and subject words). Prominently, the suggested RNN-GRU model outperforms the other techniques in every category, with exceptional accuracy of 0.90 for subject words, 0.72 for verb words, and 0.70 for object words. This shows that in terms of collecting and interpreting neural patterns associated with various linguistic components, the RNN-GRU architecture—which was created for neurolinguistic learning in non-invasive neural language decoding performs better than more conventional techniques like CSP-SVM and EEGNet. The suggested RNN-GRU model's effectiveness in comprehending and decoding complex linguistic representations from non-invasive neural signals is highlighted by the notable accuracy improvement, especially in the decoding of subject words. This highlights the model's potential to advance the fields of neural-device interaction and neurolinguistic learning. It is depicted in Fig. 6.

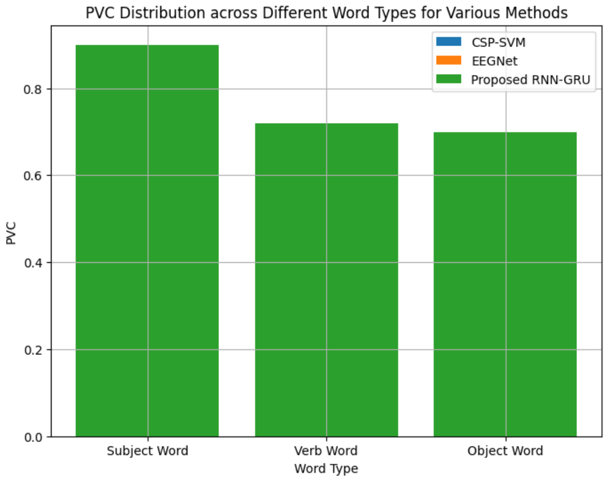

Fig. 6. PVC distribution across different word types for various methods.

E. Discussion

The study's findings, which are represented in the decoding accuracy scores for various techniques across subject, verb, and object words, offer important new information on the effectiveness of applied neurolinguistic learning strategies for non-invasive brain language decoding. Remarkably, the suggested RNN-GRU model demonstrates significant accuracy gains over conventional techniques like CSP-SVM [23] and EEGNet [24], especially in the decoding of topic words. This indicates how well the model is able to represent and decipher intricate brain patterns linked to various language components. The observed distribution of PVC performance over various word kinds clarifies the model's subtle competency and provides a thorough grasp of its flexibility to various language processing components. The area of neuro-device interaction has benefited greatly from these discoveries, which highlight the promise of deep learning techniques more especially, the suggested RNN-GRU model in improving the precision and usability of non-invasive neural language decoding systems.

The observed distribution of PVC performance over various word kinds clarifies the model's subtle competency and provides a thorough grasp of its flexibility to various language processing components. The area of neuro-device interaction has benefited greatly from these discoveries, which highlight the promise of deep learning techniques more especially, the suggested RNN-GRU model in improving the precision and usability of non-invasive neural language decoding systems. Overall, the results suggest potential directions for applications in neurotechnology and human-computer interaction, as well as advancing neurolinguistic learning approaches and laying the groundwork for future advancements in non-invasive cerebral language decoding.

VI. Conclusion and Future Scope

This research underscores the advancement possibilities in non-invasive neural language decoding through the application of a deep RNN-GRU-based neurolinguistic learning technique, thereby augmenting the capabilities of brain-device interfaces. The findings presented illustrate the superior aptitude of the proposed RNN-GRU model in capturing intricate linguistic nuances from non-invasive brain signals, outperforming traditional methods like CSP-SVM and EEGNet, particularly in decoding topic terms. The model's adaptability to diverse linguistic components is evident in the nuanced distribution of PVC performance across different word types, emphasizing its potential to enhance the accuracy and robustness of non-invasive neural language decoding systems. The flexibility of the model to various linguistic elements highlights its potential to improve the precision and resilience of non-invasive neural language decoding systems. For responsible implementation, it is imperative to handle constraints including generalizability, interpretability, and ethical issues. Neural patterns associated with language comprehension can vary across individuals, languages, and contexts. Thus, the model's performance might differ when applied to different populations or languages.

In order to further increase decoding performance, future research could concentrate on optimizing hyper parameters and fine-tuning the model for the proposed RNN-GRU architecture. Expanding the dataset to include more real-world scenarios and language components might improve the model's applicability and generalizability. Enhancing the model for real-time decoding and dynamic language processing tasks could increase its usefulness in applications like assistive technology and brain-machine interfaces. Furthermore, examining the interpretability of the model's learnt representations may yield further insights into the neurological underpinnings of language processing. It is still essential for responsible implementation to address ethical issues, such as participant privacy and the moral use of brain data.

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Post Pandemic Tourism: Sentiment Analysis using Support Vector Machine Based on TikTok Data

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***Abstract*—The tourism industry is one of the hard hit businesses during the Covid-19 pandemic and has been struggling for backup ever since. However, nowadays the industry has started to bloom again with the lifting of all of the restrictions of Covid-19. This research aims to analyze the sentiments of the tourists using the Support Vector Machine (SVM) algorithm to know their views on the tourist spots after the pandemic. The scope of the research covers the state of Terengganu which is popularly known for its islands and unique culture on the east coast of Malaysia. TikTok data has been used as the source of data as social media currently has become one of the top mediums for reviewing, selling and promoting products and services. The objective of the research is to explore the SVM algorithm in the sentiment classification of tourist spots in Terengganu. This research is expected to help the Tourism Terengganu to improve their tourist spots and their services. The phases of the research include collecting data from TikTok, data pre-processing, data labelling, feature extraction, model creation using SVM, graphical user interface development and performance evaluation. The evaluation results showed that the performance of the SVM classifier model was good and reliable, with 90.68% accuracy. The future work would be collecting more data from TikTok regularly to further improve the accuracy of the algorithm.**

Keywords—Post pandemic tourism; support vector machine; sentiment classification; TikTok data

I. Introduction

The Covid-19 pandemic has once brought tourism to stop and become one of the hardest hit businesses in the global economy [1]. However, this industry is starting to bloom again with the lifting of all the Covid-19 restrictions and also the less severe effects of virus infections. In the early days of the opening of tourism, people have been educated about the new normal procedures such as wearing masks, social distancing and sanitizing hands [2]. Since then, people have not been afraid to go anywhere in the world for a holiday getaway. Tourism is now slowly recovering and is back again as one of the country's sources of economic growth. The outbreak of the Covid-19 virus is not the biggest concern nowadays since people can get treatment if infected [3].

Terengganu is one of the states in Malaysia, located on the east coast of the Malaysian peninsular. It is a coastal state, facing the South China Sea with diverse tourist attractions such as natural tourism, cultural tourism and marine tourism. Terengganu is renowned for its islands, stunning beaches, and abundant marine life. Since the opening of the tourism businesses, social media has grown to be a very powerful information source for tourists to share their experiences. Social media such as Facebook, TikTok, Twitter and Instagram allow tourists to describe their own experience with the hotel, restaurants, and other tourist attractions. These shared sentiments have a big impact on local tourism.

Sentiment analysis (SA), also known as opinion mining is the computation of people's opinions, judgments and emotions through entities, events and attributes held by the users [4]. Sentiment analysis or opinion mining uses natural language processing and text analytics to locate and extract subjective information from source materials. To determine whether a statement indicates a positive or negative opinion towards the subject, sentiment analysis is frequently used to extract sentiments, opinions, and subjectivity from texts [5].

The ability of locals and visitors to express their sentiments is essential for the development of tourism. The expressed opinions and emotions in the reviews from social media could be extracted and analysed for the improvement of the business. Summary findings from sentiment analysis will aid tourists in selecting their tour destination and itinerary [6]. Tourists may do an information search to select the right location, which can be difficult due to the abundance of options and information on the Internet [7]. Sentiment analysis could be used to gather feedback for any tourist spots, thus helping people to choose the right vacations for them.

Based on these motivations, this research has proposed the sentiment analysis for Terengganu tourist spots after the pandemic using TikTok data. TikTok has been chosen as it has become the top medium for today's online business and socialization. TikTok is one of the social media platforms that have the power to spread news and information. Moreover, many travel and tourism companies nowadays use TikTok to promote their tourist attractions or activities. Reviews from TikTok could be classified into positive or negative sentiments. This sentiment analysis is based on the machine learning approach and Support Vector Machine (SVM) has been chosen as the classifier. SVM has proven to be able to produce good performance in sentiment classification problems [8] [9] [10] [11]. The objective of the research is to explore the capability of SVM in the classification of Terengganu's tourist spot reviews after the Covid-19 pandemic using TikTok data. The analysis results are expected to help the Tourism Agency and also the tourists to know the current conditions of the tourist spots in Terengganu, especially after the Covid-19 pandemic. This paper is arranged into five main sections which are the Introduction in Section I, Brief Literature Review in Section II, Material and Method in Section III, Result and Discussion in

Section IV and finally paper is concluded in Section V. The Brief Literature Review section provides explanation on SVM, its advantage, limitation and the previous works that have implemented the algorithm.

II. Brief Literature Review

A. Support Vector Machine (SVM)

Support Vector Machine is a global classification algorithm under the supervised learning method. SVM uses the hyperplane, which separates new inputs and produces the output [12]. The basic concept of SVM is to identify the optimum hyperplane that divides two different classes which are positive and negative classes. A separator in a d-dimensional space known as a hyperplane has d-1 dimensions. The data points closest to the hyper-plane, known as support vectors, have an impact on the hyper-position planes and orientation. The margin, or the distance between the support vectors and the hyperplane, must be maximal for the hyperplane that has been chosen. The hyper-plane can be altered by even a slight interference in the location of these support vectors. There are different types of kernel functions in SVM. The kernel's job is to accept input data and transform it into the required shape. The kernels are Linear, Polynomial and Radial Basis Function (RBF). Each of the kernels has its formula based on their concepts [13].

The advantage of SVM is that the binary classifier SVM is very efficient and has the benefit of being able to categorize with a minimal amount of information [14]. However, SVM also has its limitations such as being time-consuming when used with big amounts of data. Also, this method must be modified to classify data into more than two classes since it was designed to classify with only two classes [15]. In this research, SVM has been selected due to its suitability to process an ample amount of data and only two classes are needed in the sentiment classification.

B. Implementation of SVM Algorithm in Various Problems

SVM has been implemented in various classification problems and the results have proven to be promising. Reference [16] uses SVM, K-Nearest Neighbour (KNN) and Naive Bayes algorithm in the classification of wheat grain. This study aimed to determine the most discriminatory features and a suitable classifier that may classify the given wheat sample into classes ‘fresh’ or ‘rotten’. Since wheat is the body's principal source of energy in the form of protein, it needs to be stored with a good storage management system. The results showed that the SVM classifier outperformed other classifiers by achieving an accuracy of 93%. Another implementation of SVM was the analysis of lung cancer classification using multiple feature extraction with SVM and KNN [17]. The lung cancer was a result from the unchecked cell proliferation in a lung area. This project aimed to classify the lung CT images as normal or damaged. The results showed that SVM has achieved the highest accuracy of 96.42%.

Reference [18] has conducted a research on movie recommendation and sentiment analysis using Naïve Bayes and SVM. This project aimed to perform sentiment analysis on the movie’s reviews and to deal with the vast volume of data. The overall accuracies have shown that SVM has achieved 98.63% whereas the accuracy of Naïve Bayes was 97.33%. Reference [19] has conducted a research on sentiment analysis based on the reviews of the smartphone. There are so many smartphone products on the market which provide high-efficiency features and customers were more likely to write reviews about them. The results of this research showed that SVM has produced 79.5% accuracy. Reference in [20] has conducted a research to classify the online class student feedback in new semester. An analytical approach is required to learn the feelings of the students as they begin the new semester with online learning. In the research, the SVM method has obtained a good accuracy of 84%. Based on the previous problems, SVM has generated good performance in sentiment classification problems. Based on the algorithm’s capability, it is worth exploring the algorithm in this classification problem.

III. Material and Method

A. Experimental Data

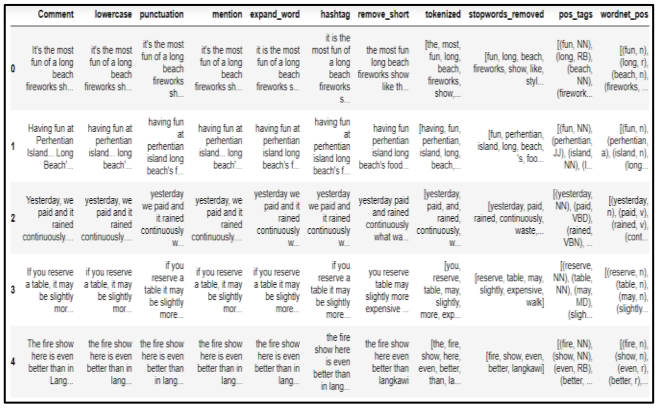
In this research, the TikTok application has been utilized to gather information for identifying tourist attractions in Terengganu. There are many tourist attractions in Terengganu such as the islands of Redang, Perhentian, Kapas, Tenggol and also on the mainland which are Pasar Payang, Taman Tamadun Islam, Batu Buruk Beach and the Terengganu State Musem. The data was collected from TikTok by using Chrome Developer Console and JavaScript has been used to automate data extraction from the TikTok website. The search keys were “Amazing Terengganu”, “Tourism Terengganu”, “Terengganu best places” and “Terengganu aesthetic”. All those keys were searched one by one, and the data scrapped was saved into the .csv file format. The data were scrapped from March to July 2023. A total of 1311 rows of reviews had been scrapped from TikTok and the data contained 11 attributes which are comment number (id), nickname, user@, user URL, comment, time, likes, profile picture URL, 2nd level comment, the user replied to and number of replies. Since this project was only focused on analysing the comments made by the user, all other attributes were discarded during the pre-processing stage.

B. Data Pre-processing

The data pre-processing is an essential part of natural language processing when it comes to text classification [21]. The unstructured data from TikTok were processed in the next stage via the data pre-processing techniques. The steps of the TikTok data pre-processing are removing duplicated data, lowercase conversion, removing TikTok mention and punctuation, tokenization and stop words removal, POS-tags labelling and lemmatization.

The first step is to remove the duplicated data from the raw dataset. The number of the raw data was 1311, which has been reduced to 1305 when all duplicated data were deleted. For lowercase conversion, the lower() method has been used to convert all of the comments to lowercase. After that, the hashtag symbol (#), user handles (@) and non-letter characters were then removed from the remark by replacing them with a blank string. These TikTok mentions and punctuation was eliminated to avoid interfering later with the main process. The next step is the tokenization and the stop words removal, which is necessary to improve the readability and transformability during feature extraction. Tokenization divides all text sentences into smaller pieces called tokens. Following tokenization, stopwords removal was applied to the clean dataset, removing stopwords from the NLTK package. The lambda function is used to eliminate the stopwords. Then, the POS tagging established the word class based on the word's placement in the sentences, indicating whether the word was a noun, adjective, verb, and so on, to allow for future lemmatization use. The POS tags of a word are necessary for correctly obtaining the word's lemma. Finally, the lemmatization step was applied to the dataset to produce meaningful root words. Lemmatization was chosen over stemming because it generated better results by analysing the word's portion and constructing actual dictionary words.

Fig. 1 shows the outcome of the data pre-processing steps, which demonstrates that most of the data have been adequately cleaned.



	Comment	lowercase	punctuation	mention	expand_word	hashtag	remove_short	tokenized	stopwords_removed	pos_tags	wordnet_pos
0	It's the most fun of a long beach fireworks sh...	it's the most fun of a long beach fireworks sh...	it's the most fun of a long beach fireworks sh...	it's the most fun of a long beach fireworks sh...	it is the most fun of a long beach fireworks s...	it is the most fun of a long beach fireworks s...	the most fun long beach fireworks show like th...	[the, most, fun, long, beach, fireworks, show,...	[fun, long, beach, fireworks, show, like, styl...	[(fun, NN), (long, RB), (beach, NN), (firework...	[(fun, n), (long, r), (beach, n), (fireworks, ...
1	Having fun at Perhentian Island... Long Beach'...	having fun at perhentian island... long beach'...	having fun at perhentian island long beach's f...	having fun at perhentian island... long beach'...	having fun at perhentian island long beach's f...	having fun at perhentian island long beach's f...	having fun perhentian island long beach's food...	[having, fun, perhentian, island, long, beach,...	[fun, perhentian, island, long, beach, 's, foo...	[(fun, NN), (perhentian, JJ), (island, NN), (l...	[(fun, n), (perhentian, a), (island, n), (long...
2	Yesterday, we paid and it rained continuously....	yesterday, we paid and it rained continuously....	yesterday we paid and it rained continuously w...	yesterday, we paid and it rained continuously....	yesterday we paid and it rained continuously w...	yesterday we paid and it rained continuously w...	yesterday paid and rained continuously what wa...	[yesterday, paid, and, rained, continuously, w...	[yesterday, paid, rained, continuously, waste,...	[(yesterday, NN), (paid, VBD), (rained, VBN), ...	[(yesterday, n), (paid, v), (rained, v), (cont...
3	If you reserve a table, it may be slightly mor...	if you reserve a table, it may be slightly mor...	if you reserve a table it may be slightly more...	if you reserve a table, it may be slightly mor...	if you reserve a table it may be slightly more...	if you reserve a table it may be slightly more...	you reserve table may slightly more expensive ...	[you, reserve, table, may, slightly, more, exp...	[reserve, table, may, slightly, expensive, walk]	[(reserve, NN), (table, NN), (may, MD), (sligh...	[(reserve, n), (table, n), (may, n), (slightly...
4	The fire show here is even better than in Lang...	the fire show here is even better than in lang...	the fire show here is even better than in lang...	the fire show here is even better than in lang...	the fire show here is even better than in lang...	the fire show here is even better than in lang...	the fire show here even better than langkawi	[the, fire, show, here, even, better, than, la...	[fire, show, even, better, langkawi]	[(fire, NN), (show, NN), (even, RB), (better, ...	[(fire, n), (show, n), (even, r), (better, r),...

Fig. 1. Data pre-processing results.

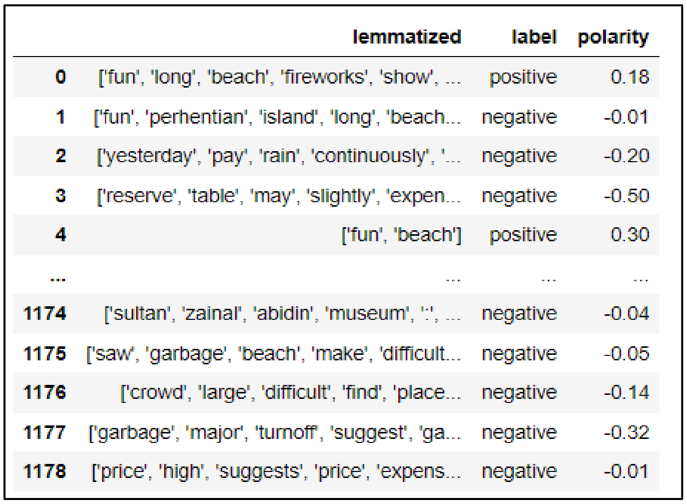
C. Data Labelling

After data cleaning, the data must be labelled to train the classifier model. Textblob is used in this project to label the text polarity to determine the text sentiment. Positive sentiment and negative sentiment are the two sentiment classes that have been assigned to the user review data. The positive class classification was based on comments that have supportive, agreeable, and positive-sounding terms. The negative class was based on user complaints or unhappiness with the situation. The dataset has been cleaned up of neutral remarks and comments that have nothing to do with the application's opinion [21].

The polarity score ranges from [-1.0,1.0] where a negative statement receives a score of -1 and a positive statement receives a score of 1. The polarity value for this project was between 1 and -1, where 1 stands for "Positive" and -1 for "Negative". Table I shows the data labelling in this research. Fig. 2 shows the result of text labelling. After removing the neutral sentiment texts, the total number of data was reduced from 1304 to 1178. This numerical labelling was done to facilitate further processing that requires numerical labels instead of textual labels.

TABLE I. DATA LABELLING

Polarity	Data Labelling	Sentiment Class
More than 0	1	Positive Review
Equal or less than 0	-1	Negative Review



	lemmatized	label	polarity
0	['fun', 'long', 'beach', 'fireworks', 'show', ...	positive	0.18
1	['fun', 'perhentian', 'island', 'long', 'beach...	negative	-0.01
2	['yesterday', 'pay', 'rain', 'continuously', '...	negative	-0.20
3	['reserve', 'table', 'may', 'slightly', 'expen...	negative	-0.50
4	['fun', 'beach']	positive	0.30
...	...	...	...
1174	['sultan', 'zainal', 'abidin', 'museum', ':', ...	negative	-0.04
1175	['saw', 'garbage', 'beach', 'make', 'difficult...	negative	-0.05
1176	['crowd', 'large', 'difficult', 'find', 'place...	negative	-0.14
1177	['garbage', 'major', 'turnoff', 'suggest', 'ga...	negative	-0.32
1178	['price', 'high', 'suggests', 'price', 'expens...	negative	-0.01

Fig. 2. Sample of labelled dataset.

D. Feature Extraction

Feature extraction helps identify characteristic sentences in tourist attractions, review data and turn them into features. The ability to produce performance in machine learning is determined by the features employed, hence the feature extraction stage was regarded as being of utmost importance [22]. The technique used for feature extraction is the TF-IDF (Term Frequency-Inverse Document Frequency) score. The TF-IDF technique is an unsupervised feature extraction method that functions at the level of a language's words or lexicon. The review text's word items are converted into numerical data using TF-IDF, making it simple for the following machine learning approach to build the classification model [23]. The term frequency (TF), inverse document frequency (IDF), and the TF-IDF score are the three calculations used to assess the significance of each word inside the data. Eq. (1) to Eq. (3) represent the three equations respectively. The TF-IDF values for each word within the dataset are collected in the corpus, creating a vocabulary of unique words. Words with high TF-IDF values are considered more important and distinctive. These words are often indicative of the specific content or theme of a document. Identifying these key features helps in understanding the focus of each document. Fig. 3 shows the sample of words and their corresponding TF-IDF values.

- Term Frequency (TF)

Using TF, one may determine how many terms are contained in a document.

$$\textit{Term Frequency, TF} = \frac{\text{Frequency of word (W) appearing in a document (D)}}{\text{Total number of words (W) in document (D)}} \qquad (1)$$

- Inverse Document Frequency (IDF)

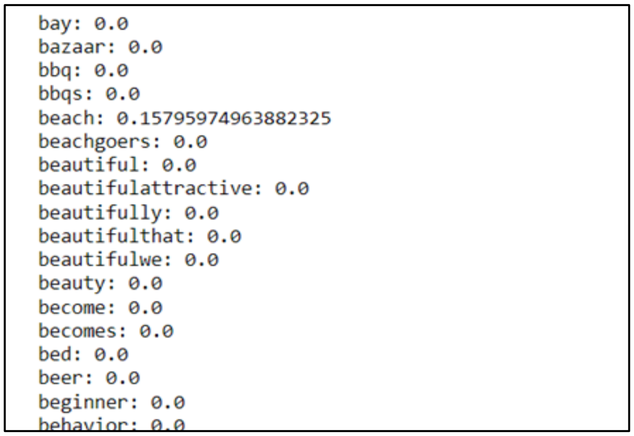
The Inverse Document Format Frequency (IDF) gives the text's uncommon words priority.

$$IDF = log_e \frac{\text{Total number of documents (D)}}{\text{Total number of document containing word (W)}} \qquad (2)$$

- TF-IDF Score

The TF-IDF score for each word is calculated. Higher-scoring words are thought to be more important, whereas lower-scoring words are thought to be less relevant.

$$TF\text{-}IDF\ (W) = \text{TF(W) x IDF (W)} \qquad (3)$$



```
bay: 0.0
bazaar: 0.0
bbq: 0.0
bbqs: 0.0
beach: 0.15795974963882325
beachgoers: 0.0
beautiful: 0.0
beautifulattractive: 0.0
beautifully: 0.0
beautifulthat: 0.0
beautifulwe: 0.0
beauty: 0.0
become: 0.0
becomes: 0.0
bed: 0.0
beer: 0.0
beginner: 0.0
behavior: 0.0
```

Fig. 3. System architecture of SVM classifier model.

E. *System Architecture*

The phases of the research include collecting data from TikTok, data pre-processing, data labelling, feature extraction, model creation using the Support Vector Machine (SVM) method, graphical user interface development and performance evaluation. Fig. 4 depicts the system architecture for the SVM classifier model. The initial phase involves data collection, where data was collected from TikTok using the Chrome Developer Console. Data pre-processing requires several phases, which include duplicate data removal, case conversion, punctuation removal, word expansion, hashtag removal, short word removal, tokenization, stop word removal, POS tag labelling, and lemmatization. The next phase is the data labelling with Text Blob, where the entire dataset will be labelled as "Positive Review" or "Negative Review." Positive reviews are labelled with the value 1, while negative reviews are labelled with the value -1. In the feature extraction phase, the dataset will be vectorized using TF-IDF technique. This is to convert the text data into numerical form so that it can be processed by the algorithm. The dataset will then be separated into two datasets, training and testing using the hold-out method. The training data is used to train the SVM classifier, while the test data is used to evaluate the performance of the algorithm. The values of accuracy, recall, precision, F1-Score and AUC are measured during the performance evaluation. The classifier model is then integrated with the graphical user interface to be used by the end user. The graphical user interface enables the system to collect user input, process the text, classify the text using the model and display the output to the user.

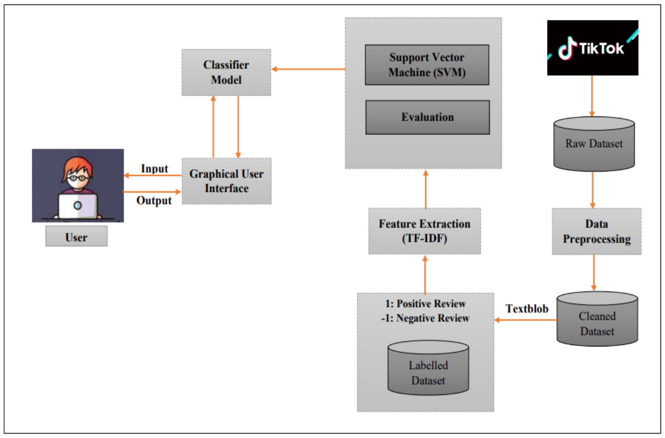


Fig. 4. System architecture of SVM classifier model.

F. *Performance Evaluation*

After building the classification model, it is important to undertake a performance evaluation to determine how accurately the suggested model produces the classification. To help the model perform better, several performance metrics could be applied. These sections explain the confusion matrix, which includes the F1 scores, accuracy, precision, recall, and ROC curve.

1) Confusion matrix: Accuracy, precision, recall, and F1 score values are computed using the confusion matrix. How accurately the model can classify objects is described by its accuracy. Precision is the proportion of correctly made positive forecasts to all correctly made positive predictions. The next step is to determine how many of the positive groups that were accurately predicted are supported by the data. The capacity to determine the number of data that would count positively for a certain attribute is known as recall. The harmonic mean between recall and precision is the definition of the F1 score. The F1 score is a statistical metric used to evaluate the average performance, depending on precision and recall [24]. A confusion matrix presents a matrix-style summary of the data set's entries based on the two standards of actual value and predicted value. The matrix's columns reflect the expected values, whereas the rows of the matrix represent the true values [25].

Confusion matrix is a technique for evaluating how well classifiers perform at each label level. It can compute the F1-measure, recall rate, precision, and accuracy rate [26]. True Positive (TP) represents the number of positive tourist attraction reviews that are correctly predicted while False Positive (FP) represents the number of positive tourist attraction reviews that are predicted as negative by the classifier. True Negative (TN) is the number of negative reviews correctly predicted and False Negative (FN) is the number of negative reviews predicted as positive by the classifier. Eq. (4) to Eq. (7) represents the Accuracy Rate, Precision, Recall Rate and F1-Measure.

- Accuracy Rate

The accuracy ratio is the number of correct samples divided by the total number of samples. The Eq. (4) below can be used to calculate the classifier's accuracy.

$$Accuracy= \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

- Precision

Precision shows the percentage of predictions for this kind of result that were accurate. The accuracy of the model prediction increases with increasing value. The Eq. (5) below can be used to calculate the precision.

$$Precision= \frac{TP}{TP+FP} \tag{5}$$

- Recall Rate

Recall is calculated as the ratio of the number of positive predictions to the number of positive class values in the test data. The accuracy of the classifiers is measured by recall, and it can be calculated with Eq. (6).

$$Recall= \frac{TP}{TP+FN} \tag{6}$$

- F1-Measure

F1-Measure effectively communicates the harmony of memory and precision. The harmonic mean of recall and precision is known as the balanced F1-score. F1-Measure obtained from the Eq. (4) below:

$$F1\text{-}measure= \frac{2*Precision*Recall}{Precision+Recall} \tag{7}$$

2) Receiver Operating Characteristic (ROC): One of the model measurement metrics is the receiver operating curve or ROC. The AUC stands for the area under the ROC curve. The performance of the model is improved by a higher AUC. It utilizes positive and negative numbers, demonstrating its capacity for classification [27]. The corresponding coordinates for the threshold's highest value are (0, 0), and for the threshold's smallest value are (1, 1) [25].

IV. Result and Discussion

In this research, the first analysis conducted was the exploratory data analysis on the collected TikTok data. The second analysis was on the performance of the Support Vector Machine Classifier. The second analysis covers the accuracy, Confusion Matrix and ROC results.

A. Exploratory Data Analysis

The labelling of the data has resulted in more positive comments than negative ones. Fig. 5 shows the number of positive comments (773) is larger than the number of negative comments (407). Some of the positive comments include beautiful beaches, nice scenery and good food in Terengganu. The most mentioned tourist spots were Pulau Redang, Pulau Perhentian, Pantai Batu Buruk, Pasar Payang, Taman Tamadun Islam, Masjid Kristal, Kuala Ibai and Muzium Negeri. There were also comments on the improvement of some of the tourist spots after the Covid-19 movement control order. The negative comments were mostly about the cleanliness of certain areas of the tourist spots. At certain tourist spots such as beaches, some irresponsible tourists were being negligent on environmental cleanliness by throwing rubbish everywhere and dirtying the places. Overall, the tourists were happy to have their holidays at Terengganu. They seemed not bothered about the Covid-19 virus which still existed in this post-pandemic. This might be because people were tired and could not care less after being in the movement control order for almost two years and fortunately the virus had also evolved to be more benign.

After processing the numeric information in the dataset, word clouds were generated for two categories: positive and negative. Word clouds are commonly used to visualize and analyse qualitative data. In this case, the comment text from the "stopword_removed" column is utilized to create the word clouds. The purpose of these word clouds is to gain insights into the main topics being discussed. Fig. 6 shows the positive word cloud, highlighting the most prominent words mentioned in TikTok comments about tourist attractions in Terengganu. The keywords include "beautiful," "Terengganu," "place," "best," "clean," "beach," "good," "view," and "island." These words suggest that users frequently mentioned these positive aspects of the tourist attractions in Terengganu in their comments.

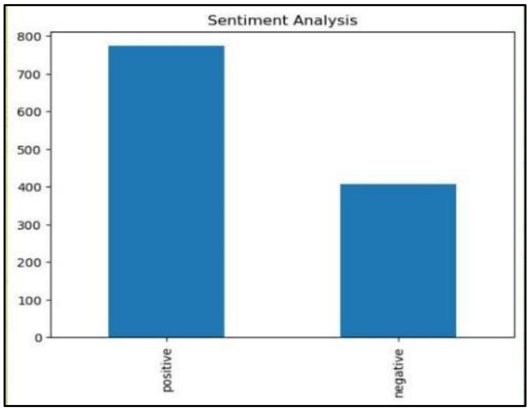


Fig. 5. Number of positive and negative comments.

On the other hand, Fig. 7 displays the negative word cloud. The words "dirty," "Terengganu",”place”, "beach," and "difficult" are considered negative, indicating that people were dissatisfied with the environmental conditions at some of the tourist attractions in Terengganu. Perhaps proper management of trash and also warning or fine should be imposed on tourists who throw rubbish at improper places.

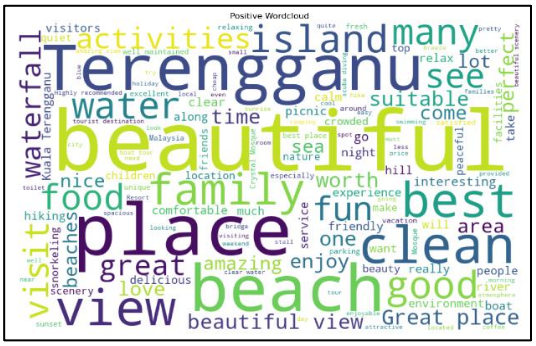


Fig. 6. Positive word cloud.

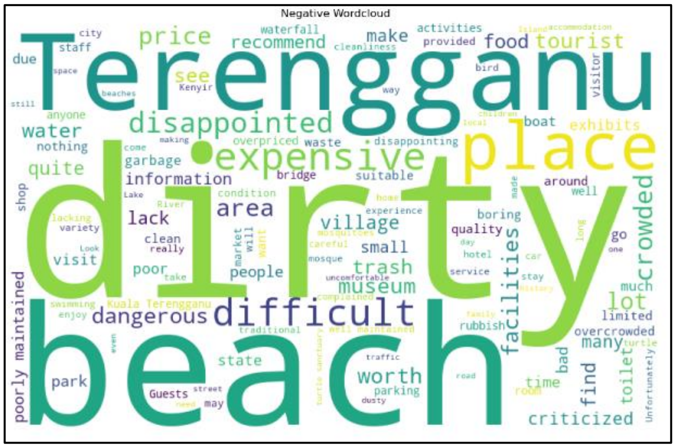


Fig. 7. Negative word cloud.

B. Support Vector Machine Classifier Performance Evaluation

This section provides the evaluation result for the performance of the Support Vector Machine (SVM) model that has been developed from scratch. The evaluation covers SVM accuracy, confusion matrix and the ROC curve.

1) SVM accuracy: In this research, the holdout method was used, and the dataset was split into the training and testing sets based on three different percentage splits: 80:20, 70:30 and 60:40. The accuracy results for each split are shown in Table II. Among the splits, the 80:20 split achieved the highest accuracy of 90.68%. Based on this result, the 80:20 split was selected for further model development since it produced the highest accuracy. Fig. 8 shows the comparison of accuracies among the data splits. In this research, the accuracy result was getting better with more data used for training. The accuracy result of 90.68% has shown that the SVM model is good and acceptable as the sentiment classifier. This is also on par with other SVM performances, as the results of SVM in other research have also produced more than 90% accuracy [16] [18] [17]. In future, the accuracy is expected to be improved if more data are scrapped and anayzed.

2) Comparison between the similar works: This section presents the accuracy of algorithms that have been implemented in similar works, which are tourism-related sentiment analysis. Table III shows the accuracy results for each of the research, using RNN, CNN, LTSM and the proposed SVM models. Based on the table, the proposed SVM model has achieved an accuracy of 90.68% which is higher than the reported RNN (80%) and LSTM (84%) accuracies. Based on this comparison, the accuracy result of the SVM model has proven to be good and able to achieve higher accuracy in its problem compared to certain deep learning models.

3) Confusion matrix: Fig. 9 shows the confusion matrix plot to illustrate the value of True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN) for negative (0) and positive (1) labels. Confusion matrix is the calculation of the correct and wrong predictions, which gives an insight into the error made by the classifier model and the type of error being made. Based on Fig. 9, 73 is the value of TP, which indicates the number of positive tourist attraction reviews correctly predicted, while the FP is 13, which was the positive tourist attraction reviews predicted as negative by the classifier. The value of FN is 9, which is the number of negative reviews predicted as positive by the classifier. Lastly, the TN value is which indicates 141 the number of negative reviews correctly predicted by the prototype. From the results, it can be observed that the model has made 214 correct predictions out of 236 predictions made. From the confusion matrix plot, it could be seen that the model has succeeded in predicting 90.68% of data in this sentiment classification problem.

TABLE II. DATA SPLIT RESULTS

Data Split	Training Data	Testing Data	Accuracy (%)
60:40	708	472	88.35%
70:30	826	354	89.27%
80:20	944	236	90.68%

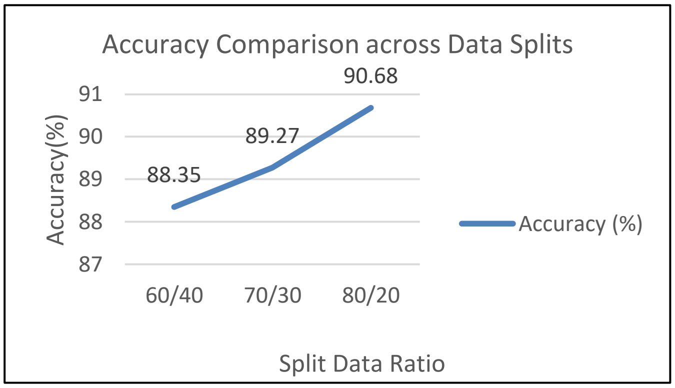


Fig. 8. Accuracy comparison among the data splits.

TABLE III. COMPARISON OF ACCURACY BETWEEN SIMILAR WORKS

Title	Algorithm	Accuracy	Reference
Sentiment Analysis in Reviews About Beaches in Bali on Tripadvisor Using Recurrent Neural Network (RNN)	Recurrent Neural Network (RNN)	80%	[28]
Convolutional Neural Networks for Indonesian Aspect-Based Sentiment Analysis Tourism Review	Convolutional Neural Network (CNN)	95.22%	[29]
LSTM-based Deep Learning Architecture of Tourist Review in Tripadvisor	Long Short Term Memory (LSTM) method	84%	[30]
Proposed SVM model	Support Vector Machine (SVM)	90.68%	-

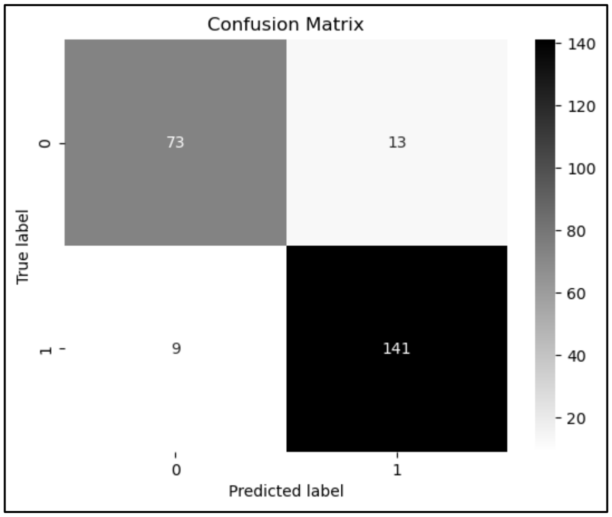
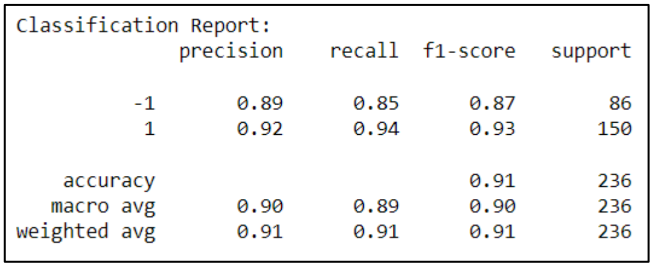


Fig. 9. Confusion matrix plot.

Fig. 10 shows the classification report of the accuracy, precision, recall and F1-score for the Support Vector Machine (SVM) classifier model. The average precision obtained was 0.92, which indicates how many instances the model correctly predicted out of all the instances. For recall, the average value is 0.94, indicating the instances that the model correctly predicted in the particular class. Finally, the average F1-score is 0.93, which represents the weighted average of precision and recall. The F1-score value has shown the good and acceptable performance of the model in correctly identifying both positive and negative instances.



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Classification Report:
              precision    recall  f1-score   support

          -1       0.89      0.85      0.87        86
           1       0.92      0.94      0.93       150

    accuracy                           0.91       236
   macro avg       0.90      0.89      0.90       236
weighted avg       0.91      0.91      0.91       236
```

Fig. 10. Classification report.

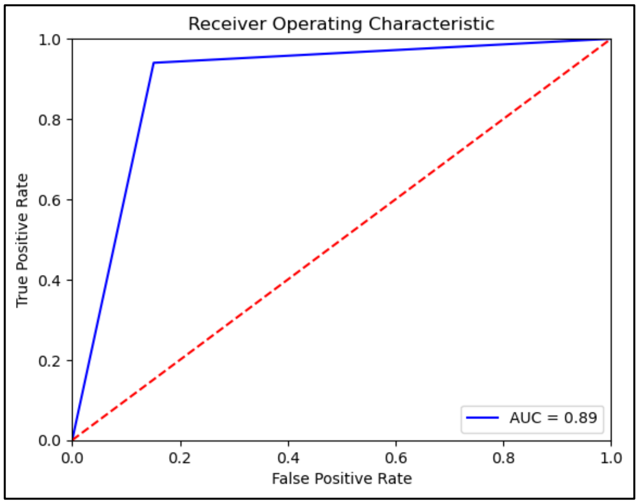

Fig. 11. ROC curve.

4) Receiver Operating Characteristic (ROC) Curve: Fig. 11 displays the ROC curve for the Support Vector Machine (SVM) classifier model. The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR). The true positive rate represents the proportion of positive observations correctly identified as positive out of all positive observations (TP/ (TP + FN)). The ROC curve's position closer to the upper left corner indicates a more effective classification of data into categories by the model. To quantify the area covered by the curve, the AUC (area under the curve) value was used. For the SVM model, the AUC calculated was 0.89, which indicates a good performance in correctly classifying data points. The AUC value could be improved more with the improvement of the true positive rate.

V. CONCLUSION

This research has met its objective in exploring the capability of SVM in the sentiment classification of the tourist spots in Terengganu after the Covid-19 pandemic era. The SVM model has produced good and reliable performance in this sentiment classification problem with an accuracy of 90.68%. In this research, the SVM model has successfully classified the tourists' sentiments and it was found that the reviews from TikTok were mostly positive about the tourist spots in Terengganu in the post pandemic. People were not afraid anymore of the Covid-19 virus and were mostly positive about coming to Terengganu for getaways. The effects of the Covid-19 virus have gradually become mild and nowadays people can do their treatments if affected. The research findings can be used by the tourism industry in Terengganu to improve the tourist spots and their services. This research also provides informed decisions about which places to visit in Terengganu, enabling tourists to choose their ideal destinations and have a memorable vacation experience. Positive feedback could significantly influence users' final decisions and make their vacation planning process easier, ensuring a smooth and well-organized trip. The recommendation for future work is to establish automated data collection techniques. This would allow the system to regularly scrap the TikTok data, enabling the model to be trained with the latest and relevant data. It is expected that this future work could further improve the classifier accuracy in the sentiment classification of the tourist spots in Terengganu. Moreover, the SVM classifier performance would also be compared with other classification algorithms such as the Naive Bayes and other deep learning algorithms.

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Investigating the Impact of Train / Test Split Ratio on the Performance of Pre-Trained Models with Custom Datasets

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Abstract—**The proper allocation of data between training and testing is a critical factor influencing the performance of deep learning models, especially those built upon pre-trained architectures. Having the suitable training set size is an important factor for the classification model's generalization performance. The main goal of this study is to find the appropriate training set size for three pre-trained networks using different custom datasets. For this aim, the study presented in this paper explores the effect of varying the train / test split ratio on the performance of three popular pre-trained models, namely MobileNetV2, ResNet50v2 and VGG19, with a focus on image classification task. In this work, three balanced datasets never seen by the models have been used, each containing 1000 images divided into two classes. The train / test split ratios used for this study are: 60-40, 70-30, 80-20 and 90-10. The focus was on the critical metrics of sensitivity, specificity and overall accuracy to evaluate the performance of the classifiers under the different ratios. Experimental results show that, the performance of the classifiers is affected by varying the training / testing split ratio for the three custom datasets. Moreover, with the three pre-trained models, using more than 70% of the dataset images for the training task gives better performance.**

Keywords—Artificial intelligence; classification; MobileNetV2; ResNet50v2; sensitivity; specificity; train / test split ratio; VGG19

I. INTRODUCTION

In our daily life, we have a huge number of generated data of different forms: text, image and video obtained from cameras and sensors. This data can be analyzed efficiently by using the advanced techniques such as deep learning. In image classification, deep learning models are used to identify special features in the images characterizing a particular class and that will help the model to distinguish between different classes. They can reach the human level performance on several fields like classifying animals, different types of food, diseases.

When having a small dataset, the best way to classify images is by using the transfer learning approach. It uses one model's knowledge on a machine learning task and reuses it as a starting point for a different but a related task. The pre-trained neural network is fine-tuned to achieve the user's needs rather than being trained the model from scratch.

Using transfer learning on image classification was introduced in the literature in several areas:

- The authors in study [1] propose the use of VGG19 architecture as the base model and complement it with different state-of-the-art techniques to classify histopathological images into IDC and non-IDC classes, Invasive Ductal Carcinoma (IDC) is a type of breast cancer.
- To identify covid-19, pneumonia and lung cancer diseases using chest radiographs, researchers in paper [2] suggest the combination of VGG-19 and Convolutional Neural Networks (CNN) to improve the performance of the multi-class classification task.
- The study presented by [3] gives different fine-tuned pre-trained models such as VGG-19, ResNet50V2 and DenseNet-121 to predict sentiments using the Twitter-based images.
- Researchers in the paper [4] gave the performance evaluation of Resnet18, Resnet50, Alexnet, DenseNet121, DenseNet201 and VGG16 models in rating gravel road images obtained from self-recorded videos and from Google Street View.
- The classification of a forest fire imagery into forest fire and no-fire was introduced in the paper [5] using a new proposed approach based on the use of the VGG19 model.
- To improve the intention classification accuracy, researchers in the paper [6] used the knowledge of the ERNIE model (Enhanced Representation through Knowledge Integration) for both: the student and the teacher models.
- The paper in [7] presents image classification and image prediction for the ImageNet dataset using the pre-trained models: MobileNet, MobileNetV2, VGG16, VGG19 and ResNet50.
- For the land use and land cover classification, transfer learning was used in the study presented in the paper [8] to fine-tune the pre-trained models: VGG16 and WRNs (Wide Residual Networks). To compare the performance and computational time, some techniques were employed such as: gradient clipping, data augmentation and early stopping. The red-green-blue version of the EuroSAT dataset was used in this work.

- The paper in [9] presents a systematic review of the early detection of Alzheimer disease (AD) by using transfer learning and neuroimaging biomarkers. In this review, five datasets were used. The researchers in this paper confirm that, for the early diagnosis of AD, the use of transfer learning technique is beneficial to develop a more accurate model.

- Transfer learning studies that uses the non-medical ImageNet datasets for medical image analysis was systematically reviewed in the paper [10]. To approach medical tasks with a non-medical dataset, the researchers suggest the use of transfer learning with ImageNet dataset. They also approve that CNN model and transfer learning technique gave reasonable performance.

- To classify mangrove communities, the study presented in the paper [11] uses three transfer learning strategies and discuss the differences in the classification task. Different models were constructed with the three deep learning algorithms: DeepLabV3+, HRNet and MCCUNet,

- For Arabic tweet classification, a transformer-based model was proposed in the paper [12]. This model was constructed from a pre-trained BERT model given by the hugging face transformer library using custom dense layers. To categorize the tweets, a multi-class classification layer was built on the top of the BERT encoder. Five publicly datasets was employed to do this study.

- The paper in [13] presents a review of the diabetic retinopathy classification with deep learning models that use transfer learning technique. According to this work, transfer learning is useful with medical image classification due to the limited number of medical images.

- To perform urban sounds classification, the researchers in the paper [14] have applied transfer learning with three datasets: UrbanSound8k, ESC-10 and Air Compressor. The pre-trained models used in this study are: GoogLeNet, SqueezeNet, ShuffleNet, VGGish and YAMNet.

- The detection of the Covid-19 disease was done in the paper [15] using the transfer learning technique with a dataset formed by X-ray images. The dataset is divided in three folders: Covid-19, pneumonia and normal (healthy) cases. Although a small dataset was used, high accuracy is achieved over all the models. The proposed approach uses VGG16, VGG19 and ResNet101 architectures.

- To categorize various food products using transfer learning, a recognition model was introduced in the paper [16]. The dataset employed in this work is Food-101. The proposed model, that uses Efficientnetb0 architecture, reaches the accuracy of 80% which is the best accuracy compared to other state of the art models.

- The study presented in the paper [17] applied the transfer learning technique for classifying monkeypox skin lesions. Six different models were employed in this work: DenseNet201, InceptionResNetV2, EfficientNetB7, InceptionV3, ResNet50 and VGG16. The paper proposes also a fine-tuned version of the InceptionV3 model named PoxNet22. The proposed transfer learning-based model gives better performance in terms of accuracy, recall and precision.

- The paper [18] gives an evaluation of pre-trained models for the detection of osteoporosis which is a bone disease in knee radiographs. VGG16 and VGG16 with fine-tuning were used in this study. The models were evaluated using accuracy, sensitivity and specificity metrics. According to this study, fine-tuning improves the VGG-16 performance for the desired task.

- Different pre-trained models for bird image identification were studied and compared in the paper [19]. The models employed are: DenseNet201, InceptionV3, MobileNetV2 and ResNet52V2. The dataset contains 58388 bird images belonging to 400 spices. All the implemented models give good accuracy but DenseNet201 was the best network, according to the authors.

- The researchers in the paper [20] confirm that the VGG16 gives a good performance with all the nine different chest X-ray datasets used. The datasets have various sizes and different class labels.

While using the transfer learning technique, the obtained model's accuracy can exceed 90% even when using datasets with less than 100 images in each class [21] just by using the correct implementation of the pre-trained model.

In a previous work [22], a performance comparison of three pre-trained models on the classification task using a custom dataset was performed. The models were trained on 30 epochs with 10^{-3} and 20 as values for the learning rate and the batch size parameters respectively. VGG19 achieved the highest accuracy, precision, recall and f1-score.

This work follows the perspective of those researches, by proposing a study of variation impact of train / test split ratio on the performance of three fine-tuned pre-trained models (MobileNetV2, ResNet50v2 and VGG19), while using a new dataset never seen by the models.

This paper is organized as follows:

Section II contains a literature review on machine learning pre-trained models. Section III introduces the pre-trained models. Section IV contains the description of the three datasets used in this study. The preprocessing phase and evaluation metrics employed for the performance comparison are described in Section V. Results and discussion is given in Section VI. The conclusion is in Section VII.

II. Literature Review on Machine Learning Pre-Trained Models

Many researches try to understand how to enhance performance of ML pre-trained models. Here are some of those studies:

- The work presented in paper [23] gives a study of the effects of dataset size and training/testing split ratios on the performance of multiclass classifiers. The results demonstrate that XGBoost gives the best performance. The performance evaluation was done using 25 performance parameters.
- The paper in [24] presents a CNN-based automatic model for the identification of the strawberry leaf plant disease like: powdery mildew leaf, healthy leaf and caterpillar pests leaf. MobileNetV3-Large and efficientNet-B0 were implemented as architecture. The dataset contains 1336 images collected from the field and the data augmentation was applied to it.
- The paper in [25] proposed a deep learning method based on CNN architecture to classify six types of strawberry plants diseases. This study utilizes 4663 strawberry leaf disease images data.
- The work presented in the paper [26] demonstrates that the use of CNN models is useful than the non-Deep learning models to distinguish between infected and healthy strawberry leaves. Under the supervision of disease specialists, the dataset (1450 images) were collected from Balamore and Millen farms Ltd.AlexNet, SqueezeNet, GoogleNet, ResNet50, SqueezeNet-MOD1 and SqueezeNet-MOD2 were employed in this study.
- The paper [27] presents an evaluation of four ensemble learning algorithms (random forest, CatBoost, XGBoost and random forest) for the prediction of heart disease using different hyperparameter optimization techniques. Three kaggle datasets were combined which had features to augment the dataset size. Using 80% of the dataset images for training was useful because the proposed model gives better accuracy while working with the train / test split ratio of 80%-20%.
- The paper [28] studied the impact of different train / test split ratios on the model performance. The ratios: 50-50, 60-40, 70-30, 80-20 and 90-10 were used in this work. The authors recommend the use of different classifiers with different train / test split ratios.

III. Pre-trained Models

A. MobileNetV2

MobileNetV2 [29] is a CNN model based on an inverted residual structure where the residual connections are between the bottleneck layers. The architecture incorporates shortcut connections to aid in training deeper networks without vanishing gradients. To improve efficiency, the model uses depth-wise separable convolution which is independently performed for each input channel. Depth-wise separable convolution reduces the complexity cost and the pre-trained model size. Due to this, MobileNetV2 has higher accuracy, needs fewer operations and is much faster than the MobileNetV1 model. The MobileNetV2 architecture (see Fig. 1) consists of 17 building blocks in a row followed by 1x1 convolutional layer, global average pooling layer and classification layer. The expansion layer role is to expand the number of channels in the data. In the projection layer, high number of dimensions is reduced to a smaller one.

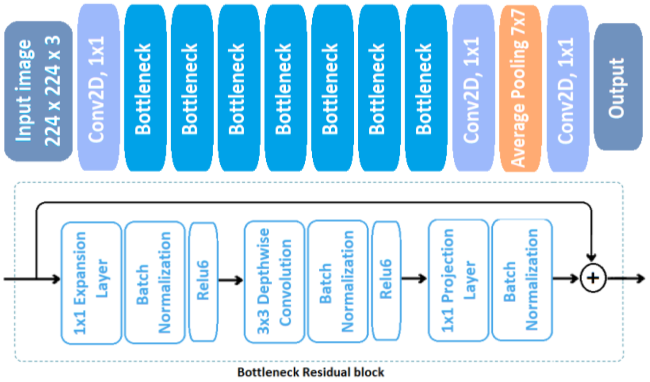

Fig. 1. MobileNetV2 architecture.

B. VGG19

VGG19 [30], part of the VGG family (Visual Geometry Group), is a CNN architecture with multiple layers. It was published by Simonya and Zisserman researchers from the Oxford University in 2014. It consists of 19 layers: 16 convolutional and three fully connected layers with a filter size of 3x3 (see Fig. 2). The number of parameters is reduced due to the small kernel size; it also enables them to cover the entire image. VGG19 was trained on the ImageNet database that contains more than 14 million images belonging to 1000 categories which helps the network to capture a diverse set of features, making it a powerful tool for the transfer learning task. For downsampling, VGG19 incorporates max-pooling layers and uses fully connected ones for classification.

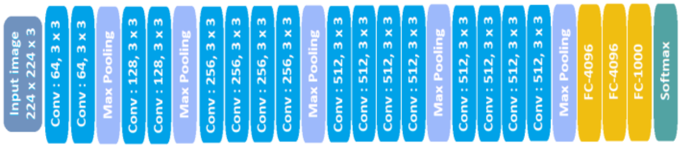

Fig. 2. VGG19 architecture.

C. ResNet50v2

ResNet50V2 [31], is a 50-convolutional neural network: 48 convolutional layers, one MaxPool layer and one average pool layer. It is known for its depth and skip connections which protect the model from vanishing gradient problem in much deeper networks. ResNet50V2 uses residual blocks which enhance the training efficiency in achieving both depth and accuracy in different tasks. To reduce the computational complexity and adjust the input layer to increase the performance of the network, ResNet50V2 utilizes batch normalization and bottleneck blocks. The ResNet50V2 architecture is shown in Fig. 3.

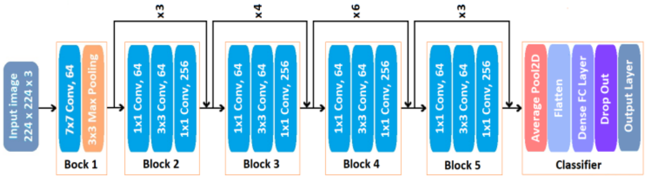

Fig. 3. ResNet50v2 architecture.

IV. Datasets

The balance (or imbalance) of the classes, which is the diversity of samples belonging to each class is a significant factor that affects the performance of classification models. Providing imbalanced data to the classifier may bias it towards the majority class because it lacks enough data to learn about the minority, which can cause false predictions. In this context, the study presented in this work was done with three balanced datasets each containing 1000 colored images divided into two classes: class_0 (500 images) and class_1 (500 images). The description of the three datasets is in Table I.

Some samples of images in the three datasets are shown in Fig. 4, Fig. 5 and Fig. 6.

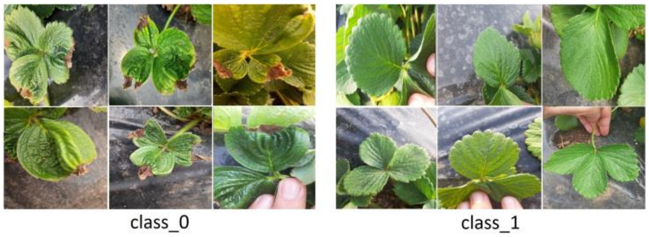

Fig. 4. Sample images from Dataset1.

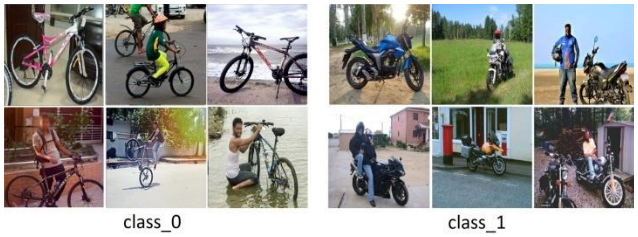

Fig. 5. Sample images from Dataset2.

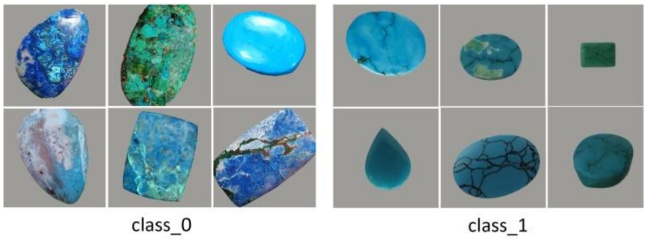

Fig. 6. Sample images from Dataset3.

TABLE I. Description of the Datasets

Dataset name	Description	Class_0 description	Class_1 description
Dataset1 (Fig. 4)	Formed from the kaggle dataset named 'Images of Strawberry Leaves for Tipburn Detection' [1]. It contains 1431 images divided into two classes: healthy (626 images) and calciumdeficiency (805 images).	Contains images of 500 images of leaves with calcium deficiency.	Contains images of 500 images healthy leaves.
Dataset2 (Fig. 5)	Formed from the kaggle dataset named 'Paribahan BD' [2]. It contains 7474 images divided into two classes: local-vehicles (7474 images grouped in 8 folders) and generated images (80 images grouped in 8 folders).	Contains 500 images of bicycles.	Contains 500 images of bikes.
Dataset3 (Fig. 6)	Formed from the kaggle dataset named 'Gemstones' [3]. It contains 6043 images divided into three classes: train (3043 images grouped in 6 folders), test and validation (each one contains 1500 images grouped in 6 folders).	Contains 500 images of turquoise gemstones.	Contains 500 images of fake-turquoise gemstones.

V. Preprocessing and Evaluation Metrics

A. *Preprocessing*

One of the major problems when training deep learning models is to have a large dataset which is not always an easy task. It is necessary to have a huge number of images in each class of several subjects of the classification. To expand the size of the three small datasets used in this work, it was beneficial to utilize the data augmentation process with the KerasImageDataGenerator class. The summarized data augmentation description is in Table II. The images have different dimensions, for this reason, they were rescaled to 224x224 pixel resolution to make them compatible with the pre-trained model's requirement.

B. *Evaluation Metrics*

In machine learning, the performance evaluation of classification models needs the use of some metrics to be able to solve real-world problems.

There are several measures to test the performance of classification results [32], the three following ones were considered in this study:

[1] https://www.kaggle.com/datasets/ercanavsar/images-of-strawberry-leaves-for-tipburn-detection

[2] https://www.kaggle.com/datasets/naifislam/paribahan-bd?select=generated_images

[3] https://www.kaggle.com/datasets/muhammadmuzamil5500/ gemstones

$$Sensitivity = \frac{TP}{TP + FN} \quad (1)$$

$$Specificity = \frac{TN}{TN + FP} \quad (2)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

TP: True Positive, TN: True Negative, FP: False Positive and FN: False Negative.

TABLE II. SUMMARIZED DATA AUGMENTATION DESCRIPTION

Name	Value / Description
Rotation_range	20
Zoom_range	0.15
Width_shift_range	0.2
height_shift_range	0.2
Shear_range	0.15
horizontal_flip	True
Fill_mode	‘nearest’

VI. RESULTS AND DISCUSSION

The pre-trained models were trained in Google Colab notebook with a learning rate of 10^{-3}, a batch size of 32 for 60 epochs. Graphics Processing Units (GPUs) was used as the model’s hardware platform.

Adam function is the simple and time-efficient optimizer for deep neural networks; thus, it has been employed for the compilation process.

The results discussed in this work are the best ones achieved from several experiments which were carried out for each case.

A. Dataset1

From Table III, it can be observed that the MobileNetV2 achieves the best sensitivity 100%) with the ratio 90%-10% and the best specificity (99%) with the ratio 80%-20%, but the best performance in terms of accuracy is obtained when using 70% of the dataset for training and 30% for testing (97.67%).

TABLE III. MOBILENETV2 EXPERIMENTATION RESULTS ON DATASET1

Train / Test ratio	Sensitivity (%)	Specificity (%)	Accuracy (%)
60% - 40%	97	97.5	97.25
70% - 30%	96.67	98.67	**97.67**
80% - 20%	93	**99**	96
90% - 10%	**100**	94	97

Looking at the plot of confusion matrix (see Fig. 7), it can be seen that MobileNetV2 model accurately predicted 293 out of 300 total samples (train / test ratio: 70%-30%).

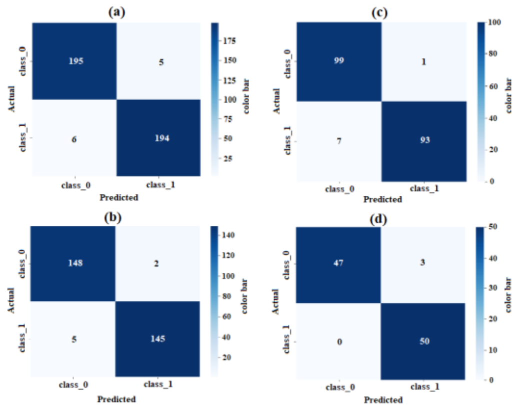

Fig. 7. Confusion matrices for MobileNetV2 with the ratios: (a) 60%-40%; (b) 70%-30%, (c) 80%-20% and (d) 90%-10%.

Resnet50V2 performs well with the Dataset1: the accuracy is greater than 97% with all train / test ratios (see Table IV). The best sensitivity score (99.5%) is observed when using 60% of the dataset for the training phase. The high specificity score (100%) is obtained with the ratio 90%-10%. But the best performance of the network is achieved with the ratio 70%-30% in terms of accuracy (98.5%).

TABLE IV. RESNET50V2 EXPERIMENTATION RESULTS ON DATASET1

Train / Test ratio	Sensitivity (%)	Specificity (%)	Accuracy (%)
60% - 40%	**99.5**	96.5	98
70% - 30%	98.67	97.33	98
80% - 20%	98	99	**98.5**
90% - 10%	96	**100**	98

ResNet50v2 classifier gives better performance with the ratio 80%-20%: it predicted accurately 197 samples which represent 98.5% of the total samples (200 samples) (see Fig. 8).

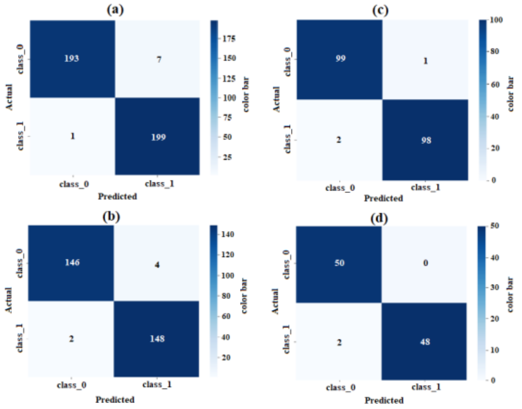

Fig. 8. Confusion matrices for ResNet50v2 (Dataset1).

Although the VGG19 classifier achieves the best sensitivity score (97%) with the ratio 80%-20% and the best specificity one (100%) with the ratio 90%-10%, the best performance of the network is observed while using 70%-30% as a train / test ratio. With this ratio (70%-30%), VGG19 reaches 97.33% for the accuracy metric (see Table V).

TABLE V. VGG19 EXPERIMENTATION RESULTS ON DATASET1

Train / Test ratio	Sensitivity (%)	Specificity (%)	Accuracy (%)
60% - 40%	94	98	96
70% - 30%	96	98.67	**97.33**
80% - 20%	**97**	96	96.5
90% - 10%	88	**100**	94

The VGG19's confusion matrix, plotted in Fig. 9, shows that the model succeeds to classify 292 samples out of all samples while using the ratio 70%-30%.

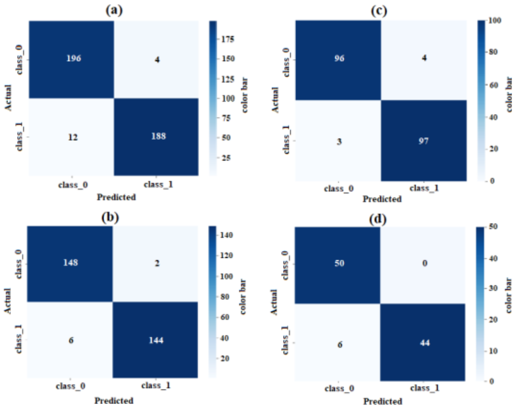

Fig. 9. Confusion matrices for VGG19 (Dataset1).

B. Dataset2

Out of all the train / test ratios, MobileNetV2 performs well with 80%-20% and 90%-10% in terms of sensitivity, specificity and accuracy with 100%, 98% and 99% respectively (see Table VI).

TABLE VI. MOBILENETV2 EXPERIMENTATION RESULTS ON DATASET2

Train / Test ratio	Sensitivity (%)	Specificity (%)	Accuracy (%)
60% - 40%	99	96.5	97.75
70% - 30%	99.33	96.67	98
80% - 20%	**100**	**98**	**99**
90% - 10%	**100**	**98**	**99**

With the ratios 80%-20% and 90%-10%, MobileNetV2 classifies accurately 99% of all the samples which is the best result obtained by this network (see Fig. 10).

The network gives better sensitivity (100%) while working with 90% of the dataset for the training phase. The better specificity and accuracy were reached with the ratio 80%-20% with scores of 100% and 99.5% respectively (see Table VII).

ResNet50v2 classifier gives better performance with the ratio 80%-20%: it predicted accurately 199 samples which represent 99.5% of the total samples (200 samples) (see Fig. 11).

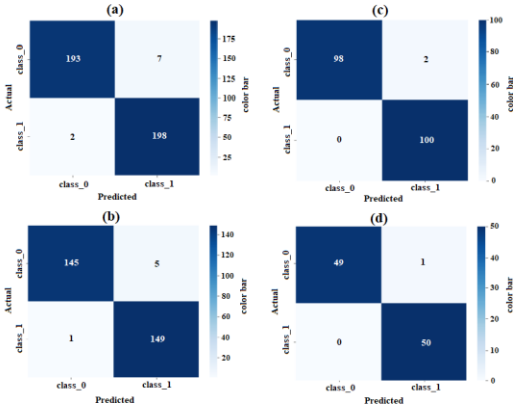

Fig. 10. Confusion matrices for MobileNetV2 (Dataset2).

TABLE VII. RESNET50V2 EXPERIMENTATION RESULTS ON DATASET2

Train / Test ratio	Sensitivity (%)	Specificity (%)	Accuracy (%)
60% - 40%	99	98	98.5
70% - 30%	99.33	96	97.67
80% - 20%	99	**100**	**99.5**
90% - 10%	**100**	98	99

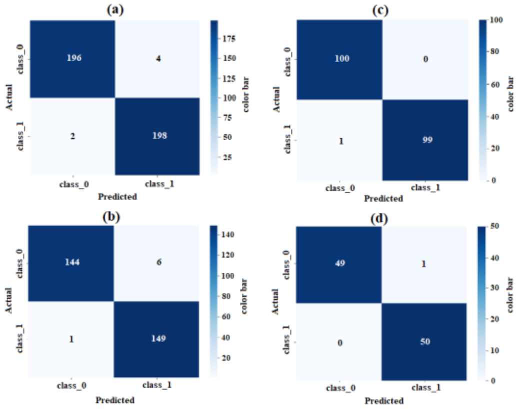

Fig. 11. Confusion matrices for ResNet50v2 (Dataset2).

The train / test ratio 90%-10% gives better sensitivity, specificity and accuracy with the score 100% for each one of them (see Table VIII).

TABLE VIII. VGG19 EXPERIMENTATION RESULTS ON DATASET2

Train / Test ratio	Sensitivity (%)	Specificity (%)	Accuracy (%)
60% - 40%	99.5	96	97.75
70% - 30%	99.33	98	98.67
80% - 20%	99	99	99
90% - 10%	**100**	**100**	**100**

The pre-trained model succeeds to correctly classify all the samples while taking 90% of the dataset for training which represent a good result (see Fig. 12).

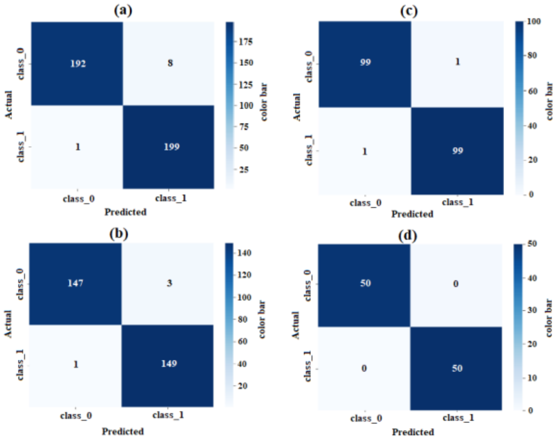

Fig. 12. Confusion matrices for VGG19 (Dataset2).

C. Dataset3

The MobileNetV2 model achieves better sensitivity (100%) with the ratios 80%-20%, and better specificity (100%) with the ratios 60%-40%. But out of all the train / test ratios, 80%-20% gives significantly better accuracy with a score of 99.5% which is a good result (see Table IX).

TABLE IX. MOBILENETV2 EXPERIMENTATION RESULTS ON DATASET3

Train / Test ratio	Sensitivity (%)	Specificity (%)	Accuracy %)
60% - 40%	98.5	**100**	99.25
70% - 30%	98.67	**100**	99.33
80% - 20%	**100**	99	**99.5**
90% - 10%	**100**	98	99

According to the confusion matrix of MobileNetV2 model with the ratios 80%-20%, it can be observed that the pre-trained model arrives to accurately predict 99.5% of all samples (199 samples of 200) (see Fig. 13).

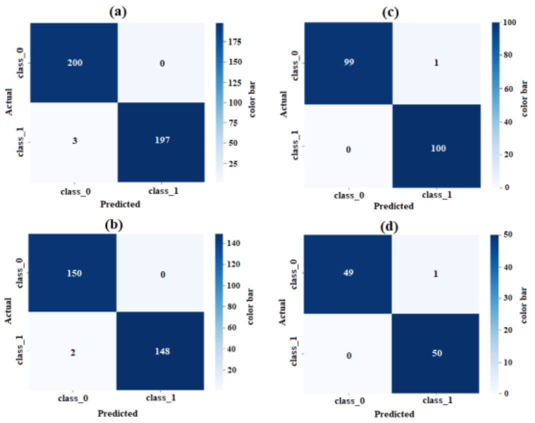

Fig. 13. Confusion matrices for MobileNetV2 (Dataset3).

With the Dataset3, the ResNet50V2 classifier achieves the perfect sensitivity, specificity and accuracy while working with 90% of the total dataset's samples for training and 10% for testing, with a score of 100% for each one of them. It also gives better specificity with the ratio 80%-20% (see Table X).

TABLE X. RESNET50V2 EXPERIMENTATION RESULTS ON DATASET3

Train / Test ratio	Sensitivity (%)	Specificity (%)	Accuracy (%)
60% - 40%	99.5	97.5	98.5
70% - 30%	99.33	99.33	99.33
80% - 20%	98	**100**	99
90% - 10%	**100**	**100**	**100**

ResNet50v2 classifier gives better performance with the ratio 90%-10%: it predicted successfully all the samples (see Fig. 14).

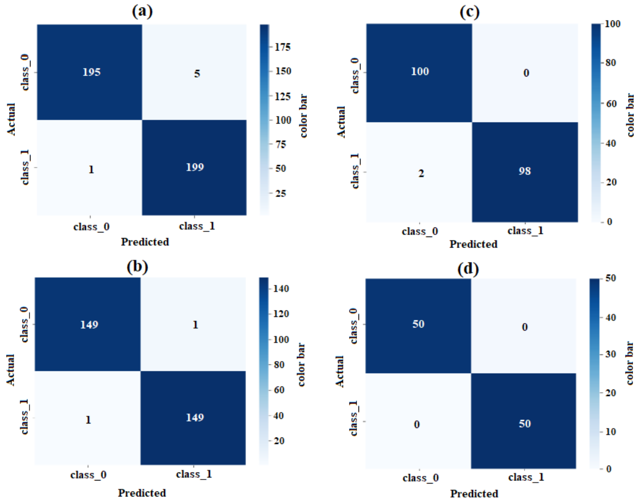

Fig. 14. Confusion matrices for ResNet50v2 (Dataset3).

With the train / test ratio 90%-10%, the VGG19 pre-trained model gives better performance in terms of sensitivity, specificity and accuracy with a score of 100% for each one of the metrics (see Table XI).

TABLE XI. VGG19 EXPERIMENTATION RESULTS ON DATASET3

Train / Test ratio	Sensitivity (%)	Specificity (%)	Accuracy (%)
60% - 40%	97.5	99.5	98.5
70% - 30%	98	99.33	98.67
80% - 20%	98	**100**	99
90% - 10%	**100**	**100**	**100**

The VGG19's confusion matrix, plotted in Fig. 15, shows that the model succeeds to classify correctly all the samples while using the ratio 90%-10%.

The results show that the best performance achieved with the networks was when using the train / test ratios 80%-20% and 90%-10%. While working with the ratio 60%-40%, all the classifiers couldn't give better scores in terms of sensitivity, specificity and accuracy, as well as the other ratios. The three networks need more than 70% of the dataset's samples for the training phase to give better results.

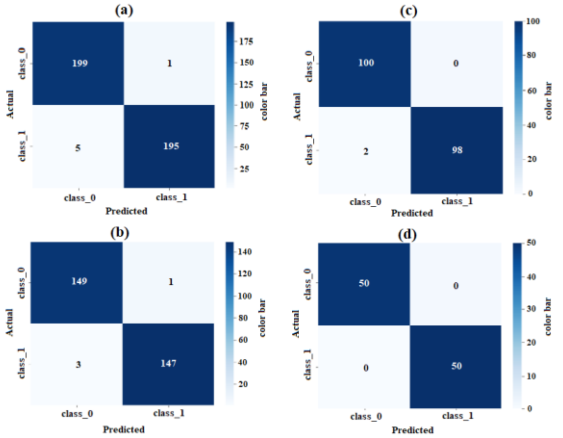

Fig. 15. Confusion matrices for VGG19 (Dataset3).

VII. Conclusion

This study was realized with three datasets never seen by the pre-trained models: MobileNetV2, ResNet50 v2 and VGG19. The datasets were divided in two classes (class_0 and class_1). For all experiences, the batch size was fixed at 32 and the learning rate at 10^{-3}. All the experiences were for 60 epochs. Analyzing the results, it can be observed that the train / test split ratio has a significant impact on the classification performance of the three pre-trained networks: MobileNetV2, ResNet50v2 and VGG19, the ratios 80%-20% and 90%-10% gives better results on the most cases.

All the pre-trained networks used in this study performs well with the Dataset3, this is due to its simplicity in comparison with the other datasets (Dataset2 and Dataset3). It has less features to be learned by the models which facilitate the learning process and enhance the classifier's performance.

In conclusion, increasing the size of the train data enhanced the performance of the three classifiers; more than 70% of the dataset's samples is required in the training phase to achieve better performance.

For future work, other datasets with different sizes will be studied using the three pre-trained models to have a more generalized conclusion concerning the impact of the train / test split ratio on the performance of the networks. Other architectures could be also added to the study. The impact of using several optimizers will be investigated for different pre-trained models and different datasets.

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Action Recognition Method of Basketball Training Based on Big Data Technology

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***Abstract*—Aiming at the problem that improper posture of basketball players leads to not obvious sports effects, the present paper proposes an action recognition method combining computer vision and big data technology and applies it to athletes' daily training and competition. Firstly, based on the current mainstream motion recognition models, 3D graph convolution are used to improve the original 3D convolution to promote the expression ability of spatial structure features and temporal features in skeleton sequences. Secondly, channel and spatial attention mechanisms are introduced to focus on the weight distribution of key points and strong features in different posture recognition processes. Finally, the proposed model is tested in real data, and the test results show that the model runs smoothly while maintaining high recognition performance. It can more effectively direct basketball players to implement comprehensive, systematic, and scientific teaching and training standards that directly support raising the game's general level of performance.**

Keywords—Action recognition; computer vision; big data technology; three-dimensional convolution; channel and spatial attention mechanisms

I. Introduction

Accurately identifying and evaluating athlete movements is crucial in basketball training. However, traditional action recognition methods often rely on manual observation or simple video analysis tools, which not only have low efficiency but also cannot guarantee accuracy. Basketball is a highly complex competitive sport that requires athletes to possess superb skills and tactical understanding. In order to achieve the best training results, coaches and athletes need a method that can accurately and efficiently identify and evaluate athlete movements. Traditional action recognition methods mainly rely on manual observation, which is not only time-consuming but also susceptible to subjective factors. With the development of big data technology, the accuracy and efficiency of machine learning and computer vision algorithms have been significantly improved, providing new possibilities for solving this problem. Due to the continuous development of the social economy and science and technology, intelligence has been more and more widely concerned about and studied and is gradually becoming a global trend. With the arrival of the information age, many intelligent devices have become accessible to people, which greatly facilitates people's lives and further promotes the development of relevant research fields. In recent years, research on artificial intelligence has made remarkable progress. Machine vision is the main branch of artificial intelligence, and human behavior recognition is one of the important research directions [1]. Visual human behavior recognition includes the following parts: Acquisition of human behavior video sequence, feature extraction of moving human body, learning and recognition of classifier, among which feature extraction and classification recognition is the main research content of human behavior recognition [2].

Visual human behavior recognition and analysis is a comprehensive research direction; from the theoretical level, human behavior recognition research involves a variety of theoretical disciplines, including pattern recognition, statistics, information processing, computer vision, and so on. The research significance of human motion behavior recognition is mainly reflected in its practical value. With the continuous progress of video acquisition sensors and information science and technology, the research of motion behavior recognition has gradually become a subject with wide application prospects in many fields. It has been successfully used in basketball training, football training, alpine skiing, running, and other sports movement recognition because of its portability, wireless, and easy-to-operate characteristics [3]. However, in competitive competition, the limitation of experimental conditions leads to great challenges in capturing the above movements. Because of the quick development of computer vision and big data technology, it is important to use the new technology to effectively capture the training movements of basketball and football players, help them improve their disharmonious movements quickly, and improve their comprehensive quality.

Recent advancements in computer vision-based motion capture technology have made it possible to recognize human activity in challenging environments. Unmarked motion capture was carried out by camera equipment to obtain kinematics information remotely in the competition. Based on computer vision machine learning algorithms, human actions are displayed as waveforms corresponding to specific actions that are downloaded to a computer terminal. Subsequently, the synchronous video analysis, information extraction, and quick feedback are finished. Motion analysis based on a computer vision image must first predict or estimate the target's position and direction within the image sequence. Real-time tracking and displacement parameter acquisition are then accomplished by locating the target in the continuous image that has the same or comparable features. The human body is typically represented in practical applications as a collection of rigid bodies joined by frictionless revolute joints because this makes machine recognition and tracking easier. However, because human movements involve soft tissues like tendons and ligaments, they are too complex to be fully understood by a rigid, simple body model. Thus, one of the challenges facing specialists in computer vision, machine learning, and sports science is precise tracking and measurement of dynamic human posture.

A deeper neural network model structure characterizes deep learning. The majority of the algorithms use manually labeled image data to train the neural network and then input the image or video into the trained network to estimate and recognize human posture, joint center, and bone position. In particular, skeleton behavior recognition technology is a method to understand and describe human behavior by extracting the action features in a skeleton sequence. Skeleton behavior recognition is one of the hot research directions in the field of machine vision. It can realize the accurate recognition of the motion of the target object by the computer, then analyze the motion of a human body in the video, and improve the dynamic perception ability of the computer. To evaluate the advantages of our method over existing methods, we conducted experimental comparisons on publicly available datasets. The results show that basketball training action recognition methods based on big data channels and spatial attention mechanism technology have significant advantages in accuracy, efficiency, and applicability to real-world scenarios. Compared with traditional methods based on manual observation or simple video analysis, our method greatly improves the accuracy and efficiency of recognition, reducing the need for manual intervention. Meanwhile, when compared with other deep learning models, our method better processes spatial information in videos by introducing spatial attention mechanisms, further improving the performance of action recognition. The basketball training action recognition method based on big data channels and spatial attention mechanism technology provides an efficient and accurate means of action evaluation for basketball training. This method can not only be applied in the field of basketball training, but can also be extended to other sports or general video action recognition tasks. Future work will further optimize the model structure, explore more effective attention mechanism methods, and apply this technology to practical training scenarios to verify its performance and effectiveness in the real world.

Section I of this article first analyzes the application background of machine learning and computer vision algorithms, which are of great significance for capturing the training movements of basketball players.   Section II analyzed the comprehensive temporal dynamic information of bone sequences under different attention mechanisms of network applications. Section III proposes a method for action recognition using computer vision technology and big data technology, and applies it to action recognition in basketball player training. Section IV uses a 3D graph convolution module to extract spatiotemporal information from the skeleton sequence. We have established an attention enhancement structure to help nodes focus on key action information and pay more attention to certain areas. Finally, a behavior recognition model was constructed by combining 3D convolution with attention enhancement structures. Section V summarizes the entire text. The P-R curves of the model in this article can all surround the P-R curves of the comparison model, indicating that the overall action recognition performance of the model in the current study has been improved to varying degrees after using 3D graph convolution and attention mechanism to improve the existing model.

II. Related Works

Human motion recognition research is getting more and more advanced as a result of the steady advancement of deep learning, machine learning, and other related technologies. The research and application of human motion recognition based on attitude sequence are different from tasks such as image recognition and target detection. The research on human motion recognition is related to time sequence. Input data includes spatial dimension and time dimension, so compared with other fields of computer vision, the difficulty and challenge of action recognition are greater.

A. *Motion Recognition Based on Human Bone Sequence*

Dynamic human skeletons often contain a wealth of information and best represent human movement and behavior. The motion recognition algorithms based on the human bone sequence are usually divided into four categories: manual feature-based method, RNN/LSTM-based method, CNN-based method, and graph convolutional Neural network (GCN) based method.

Using the geometric relationships found in the space structure of the human skeleton for motion recognition is the aim of the traditional manual feature design method. Literature [4] listed nine geometric features, including eight static features and one time feature. The static feature encodes the form of motion and posture and uses the time feature to represent the change in time. The study in [5] proposed the use of the rotation and displacement of human bones to represent the three-dimensional transformation relationship between various body parts. The research in [6] proposed an integral invariant used to represent the motion trajectory of bone points and matched the motion trajectory. A collection of geometric characteristics, such as the separation between joints and the distance between joints to the plane formed by joints, were taken from study [7] and used to characterize posture and movement. While designing features, it is impossible to account for every factor so that most experimental results could be improved. Deep learning and other data-driven methods have gained popularity recently. Among them, the most popular models are CNN, GCN, and RNN/LSTM.

The main advantage of RNN/LSTM is that context dependencies can be modelled in the time domain. In addition, in the RNN/LSTM-based approach, the bone sequence is modeled as a coordinate vector of a series of joints, each coordinate representing a human joint. The study in [8] proposed the STA-LSTM network, which applies an attention mechanism to choose discriminating patio-temporal features, key joints, and keyframe information, respectively. The research in [9] proposed a VA-LSTM network. In VA-LSTM, two sub-networks were used to return parameters of rotation and translational matrix for rotating and translational bone coordinates to appropriate observation directions. Then, the new observed bone was input into the three-layer LSTM main network for motion recognition. The study in [10] proposed a

GCA-LSTM network and introduced global context memory to generate attentional representations for optimizing global context information. The SR-TSL approach was first presented in study [11] in 2018. It uses a time stack learning network (TSLN) to gather comprehensive temporal dynamic information on the bone sequence and a spatial inference network to gather high-level spatial structure information. The study [12] converted the input skeleton into several possible visual observation values, which were respectively processed by the attention LSTM network and finally fused with the output to generate recognition results.

In contrast to RNN/LSTM, the CNN-based method can learn spatial and temporal features simultaneously. The method based on CNN is used to encode bone sequences as pseudo-images (RGB or grayscale images) and time series as rows of bone joints in the image as columns. The study in [13] proposed to encode five spatial skeletal features as pseudo images and further explore space-time information by using CNN. The study in [14] proposed a new bone sequence representation method, which transformed a bone sequence into three fragments corresponding to the joint coordinate channel, and each fragment was composed of several grayscale images. The generated fragments are then fed into a deep CNN model for motion recognition. The research in [15] converted the transformed bone sequence into an RGB image, regarding the coordinates of the bone sequence (X, Y, Z) as the coordinates of the color image (R, G, B), and designed an arrangement network for data rearrangement. The study in [16] proposed an HCN model that can learn global co-occurrence features from skeletal sequences. This network combines graph convolution with LSTM, replaces the internal LSTM operations with graph convolution operations, and uses an attention mechanism to strengthen key node information while weakening non-key node information, highlighting more discriminative spatial features.

Recently, the GCN-based graph convolution network has attracted extensive attention because of its more natural representation of bone structure than based on RNN and CNN. In 2018, the research in [17] first developed a new deep learning model, namely space-time graph convolutional network (ST-GCN), which directly modeled bone data as graph structure, in which natural connections of human bones constitute spatial edges and corresponding joints in adjacent frames constitute temporal edges. Based on ST-GCN, the study in [18] used a frame distillation network to select keyframes and then sent the selected keyframes into a graph convolution network for action recognition. However, the spatial diagram in ST-GCN is fixed, and only human joints with natural connections are considered at the spatial edges. Moreover, it also proposed a multi-flow adaptive graph convolutional network (MS-AAGCN), which introduced an attention module and multi-flow network into 2S-AGCN. The study in [19] used the residual attention module to identify key joints. In contrast, the attention module used the original RGB image as input to generate attention masks to emphasize the areas that are important for emotion recognition in a frame. The research in [20] proposed that context information in original RGB videos should be used to extract joints with not only richer information but also highly relevant context information. At the same time, it used a neural structure search (NAS) algorithm to construct a graph convolutional network based on bone action recognition.

B. *Behavior Recognition in Sports*

The integration of human behavior recognition and attitude estimation technologies into display application scenes led to the gradual introduction of these technologies into intelligent sports analysis systems. Hoop Tracker is a smart basketball analytics system that works with smart wear. The hoop tracker has a speed sensor that detects every shot. The shot detector is made into a patch, fixed inside the basket, through which the ball passes after each goal. Each time the shooter takes a shot, the watch and the shot detector communicate in real-time to see how far the shooter is from the basket and whether the ball hits. The system displays data on shots, three-pointers, and free throws, as well as field goal percentage and points. Shot Tracker’s smart system, called Shot Tracker Team, has smart sensors attached to basketballs and players' shoes. In addition, the basketball court and the top of the court are surrounded by sensors, so the players are in a space without dead space [21]. These sensors give real-time feedback on the position of the player and the ball. Through the intelligent equipment, real-time analysis is made according to the data of players and ball movement on the court. The comparative information on the advantages and disadvantages of each player in the game is displayed in the form of data, including the analysis of players' shooting times, mistakes, assists, steals, dunks, and other actions. This data not only shows the players on the court to the audience but also provides the on-court coach with a data-backed tactical plan. In addition, in daily training, players can also use this system to let them understand their strengths and weaknesses to help adjust their targeted training. Most of the above products rely on smart wearable devices to capture and analyze athletes' movements. However, in general competitions, smart wearable devices will have a certain influence on athletes' competitions, and the sensors of smart wearers will have various uncertainties of system accuracy. NBA, as the highest professional basketball game in the world, mainly uses computer vision as a single information capture method of the Sport-VU system. The system has six 3D high-definition cameras fixed to the ceiling of each arena. Each camera takes pictures at high speed and sends them to a computer for data analysis. These cameras work at 25FPS. The software records and analyzes the player's movement trajectory and other information to obtain all kinds of technical and tactical data such as scoring, steals, rebounds, assists, instant speed, and so on.

III. Behavior Recognition Model based on 3D Graph Convolution and Attentional Enhancement

A. *Three-Dimensional Convolution with Graph Convolution*

1) 3D-convolution: The basketball training action recognition method based on big data technology mainly relies on data collection, feature extraction, and action classification. Firstly, this article collects a large amount of basketball training video data, including various movements of athletes. Then, computer vision algorithms are used to preprocess these videos and extract key motion features. Finally, machine learning algorithms are used to classify and recognize these features.

Specifically, this method combines deep learning and computer vision techniques, utilizing convolutional neural networks (CNNs) to identify and extract key information from videos. In order to better understand and recognize various actions in basketball training, 3D Convolutional Neural Network (3D CNN) was adopted, which can better process spatial and temporal information in video sequences. In the action classification stage, attention mechanism is introduced. The attention mechanism allows the model to focus on key information regions when processing complex basketball training videos, thereby improving the accuracy of action recognition. By integrating 3D graph convolution and attention mechanism, the method proposed in this paper has higher efficiency and accuracy in handling basketball training action recognition tasks. Sample areas at the same location in several consecutive frames make up the 3D sampling space of 3D convolution [22], which contains two dimensions: time and space. Through the three-dimensional convolution kernel, stack and sum the data of the sampling area in multiple consecutive frames to generate multidimensional data, thus realizing the convolution operation of the three-dimensional sampling space, as shown in Fig. 1. Given that the convolution kernel size of the three-dimensional convolution kernel is $[P_i, Q_i, R_i]$; thus, the position response of the JTH feature graph in the layer I network can be expressed as Formula (1).

$$u_{ij}^{xyz} = \sigma(b_{ij} + \sum_{p=0}^{P_i-1}\sum_{q=0}^{Q_i-1}\sum_{r=0}^{R_i-1} w_{ij}^{pqr} u_{(i-1)j}^{(x+p)(y+q)(z+r)}) \tag{1}$$

where, P_i and Q_i are the two spatial dimensions of the three-dimensional convolution kernel, R_i is the time dimension of the three-dimensional convolution kernel, u_{ij}^{xyz} represents the sampling weight in the three-dimensional convolution kernel, and b_{ij} represents the bias value; The A function contains operations such as batch standardization and activation functions.

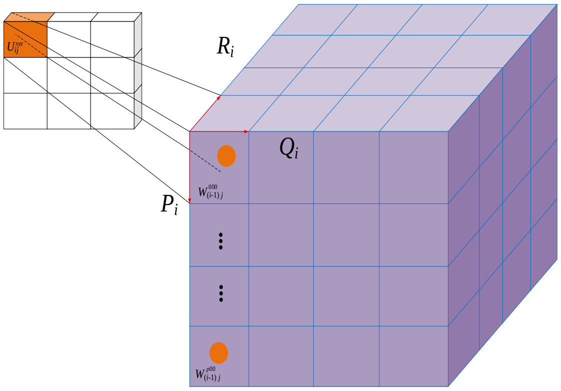


Fig. 1. Schematic diagram of the three-dimensional convolution operation.

3D sampling can not only collect spatial information but also build the connection between the current feature map and multiple consecutive frames in the output of the previous layer by weighted superposition of multiple consecutive frames in the output of the previous layer, realizing the capture of time information in the range of multiple frames. Therefore, 3D convolution can not only realize the collection of spatial and temporal information at the same time but also retain the correlation between the two. Therefore, the 3D convolution can be applied to the collection of spatial-temporal features of 3D sequential data in European space, such as continuous motion video frame sequence.

2) Graph convolution: Graph convolution is a general and effective way to learn graph structure data. Graph convolution aggregates information of neighbor nodes by weighted summation of hidden states of neighbor nodes through graph convolution kernel, which can process variable length neighbor nodes, realizes the convolution operation of graph structure data, and extracts information on a graph. Therefore, graph convolution can process graph structure data with generalized topological structure, so it is widely used in skeleton behavior recognition and attitude estimation.

Suppose there are m nodes in the output graph of layer *L* network, and the n-dimensional hidden state from the first node to the *m*-th node is represented $h_1^l, h_2^l, \ldots, h_m^l$, as shown in Fig. 2. The node states in the figure are denoted as $H^l[h_1^l, h_2^l, \ldots, h_m^l] \in R^{m\times n}$, and an adjacency matrix can represent the connection relationship $A \in R^{m\times n}$, so the first node in the output of the layer $l+1$ responds with 1, which is expressed as Formula (2).

$$h_1^{l+1} = \sigma(b + D^{-1/2} \otimes A \otimes D^{-1/2} \otimes H^l \otimes W) \tag{2}$$

where, D represents the degree matrix of A, a is the element of A to judge whether the node is A neighbor node with connection, W refers to the weight matrix of graph convolution, B is the bias value, $\sigma(\cdot)$ represents the activation function of nonlinear variation.

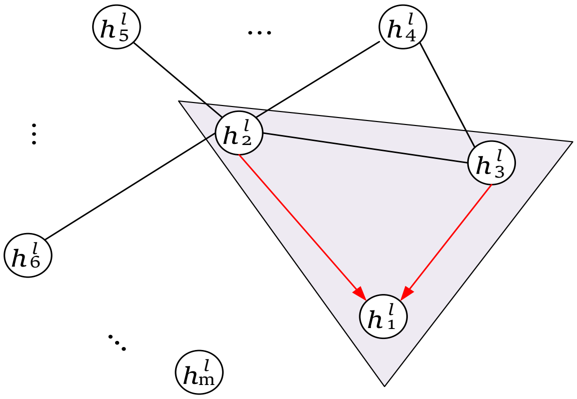


Fig. 2. Schematic diagram of the graph convolution operation.

3) 3D graph convolution: It is impossible to analyze the correlation between the spatial structure features and temporal features of skeleton sequences separately because they can describe all of the action information in the sequences together. Accordingly, the three-dimensional graph convolution method needs to be investigated to achieve the effective extraction of spatial-temporal information from the skeleton sequence.

In particular, the 3D sampling space in 3D convolution is rasterized sampling, which is only suitable for the feature collection of 3D sequential data in Euclidean space [23]. For 3D data in non-Euclidean space, the number of neighbor nodes in the sampling space is not fixed. Therefore, 3D convolution cannot extract spatial-temporal information from skeleton sequences with non-Euclidean three-dimensional data; Graph convolution can only extract spatial information on a graph through graph convolution kernel, which is capable of handling neighbor nodes with varying lengths. A three-dimensional graph convolution method is proposed in this paper to extract spatial and temporal information of three-dimensional skeleton sequences in non-Euclidean space. The technique is predicated on the graph convolution kernel, which is capable of managing neighbor nodes with varying lengths in graph convolution. Using the 3D sampling space in 3D convolution as an improvement idea, the 2D graph convolution kernel is improved to the graph convolution kernel with three-dimensional sampling space.

In the model process of the three-dimensional graph transformation based on the skeleton order, the adjacent nodes in the three-dimensional model space contain two adjacent nodes connected to the node in the skeleton stream and nodes close to the same point in several consecutive frames. Based on the three-dimensional graph convolution kernel, the three-dimensional graph convolution of the skeleton sequence is realized by weighted stack summation of neighbor node data in three-dimensional sampling space to generate multidimensional data, and the spatial-temporal information of the skeleton sequence is extracted effectively. As shown in Fig. 3, suppose L continuous skeleton frames in the three-dimensional sampling space. From frame 1 to frame L is denoted as $G^0, G^1, \ldots, G^{L-1}$ then the output result of three-dimensional graph convolution can be expressed as Formula (3).

$$x' = \sigma(b + \sum_{t=0}^{L-1}\sum_{c=0}^{C-1}\sum_{k=0}^{K-1} D^{-1/2} \otimes A \otimes D^{-1/2} \otimes G_{c,k}^{t} \otimes W_{c,k}^{t}) \tag{3}$$

where, A indicates the adjacency matrix of the connection relation, D denotes the degree matrix of A, $G_{c,k}^{t}$ is the characteristic value of channel C of the KTH neighbor node of frame T in the three-dimensional sampling space, $W_{c,k}^{t}$ refers to the weight matrix of three-dimensional graph convolution, b is the bias value; The $\sigma(\cdot)$ function contains operations such as batch standardization and activation functions.

B. Attentional Mechanism

1) Channel grouped attention: Channel grouping attention groups channel features and highlight salient features in each group by using the similarity between both local and global features. Fig. 4(a) presents the network layer structure of channel-grouped attention. Features are divided into G groups according to channels, and the input features of each group are fused with the feature map G containing a semantic vector after global average pooling to form a new feature map. After normalization and sigmoid activation function operation, the input features of each group are integrated with the original feature by the site. According to the definition of the dot product, $g \cdot x_i$ can be written as $\| g \| \| x_i \| cos\theta_i$, where θ_i is the Angle between g and x_i. Therefore, the feature of the modulus length and the feature that is close to the direction of the global feature vector will get a larger initial attention coefficient. At the same time, attention values of different samples vary greatly, so they need to be normalized to the same range to give accurate attention weight.

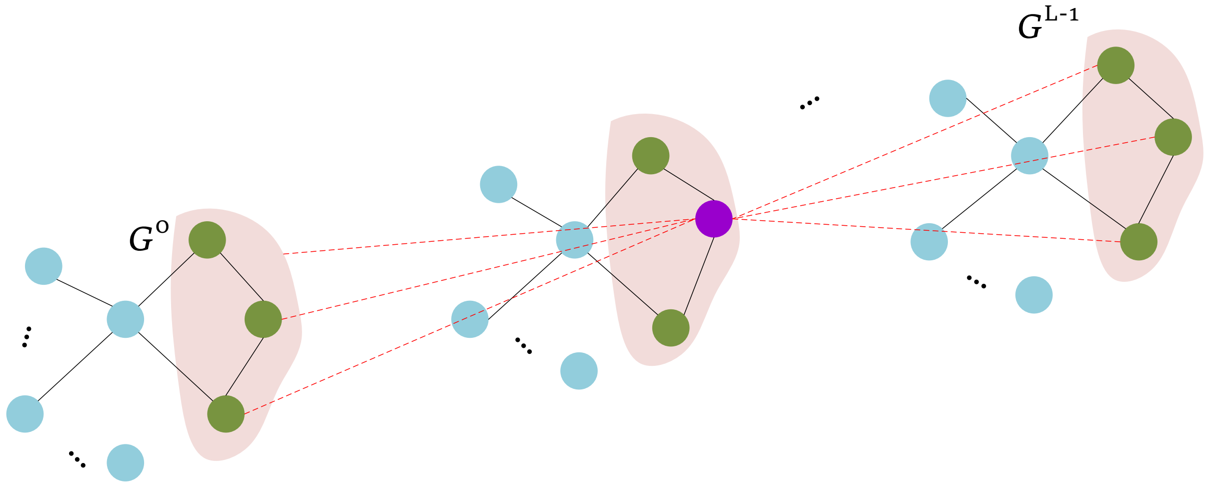


Fig. 3. Schematic diagram of 3D graph convolution operation in skeleton sequence.

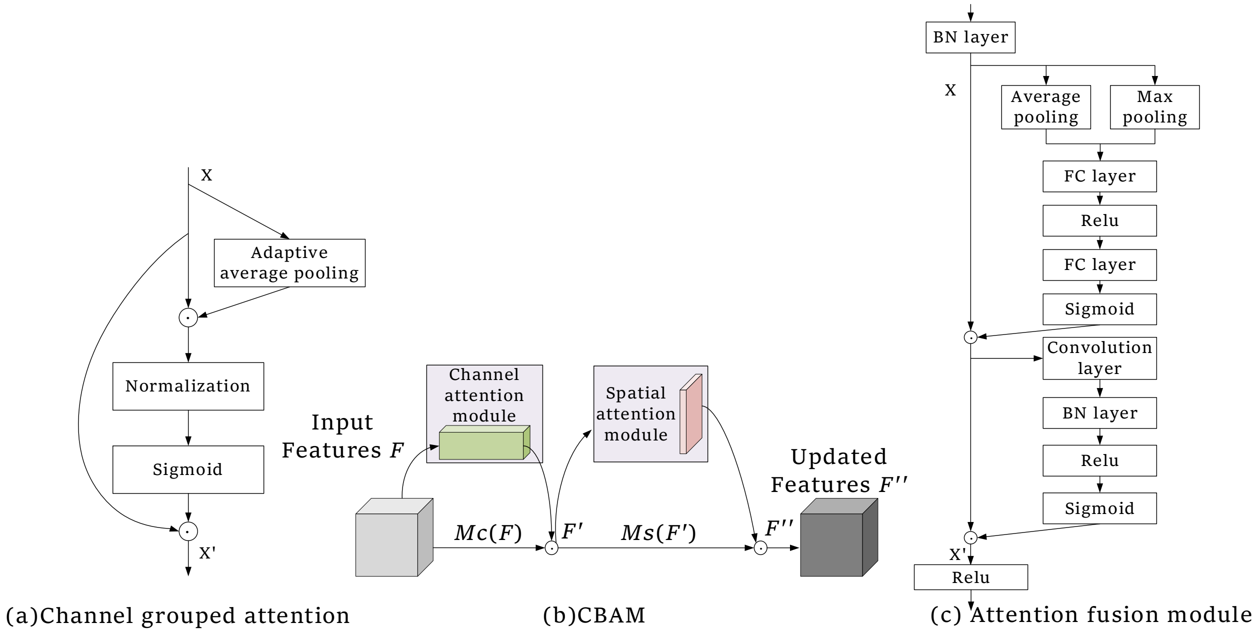


Fig. 4. Each attention mechanism module component.

2) Channel-spatial attention: CBAM attention network [24] is analogous to the human visual attention mechanism, which reconstructs the feature matrix through channels and Spaces. A self-learning method is adopted to recalibrate the weights of features. The overall network structure of CBAM is shown in Fig. 4(b). The feature F extracted from the input image was dotted with the feature $M_c(f)$ after the action of the channel attention module to obtain the feature F'. Similarly, the improved feature F'' was obtained through the action of the spatial attention module. The sequential connection of the channel attention module and spatial attention module is more effective than the parallel connection.

Unlike the channel attention module, which concentrates on the context in which the information is meaningful, the spatial attention module is location-specific. The channel attention module and the spatial attention module complement each other, focusing on location and content respectively and linking sequentially [25]. Similar to the channel attention module, for the H×W×C input feature F', the maximum pooling and average pooling of channel dimensions are firstly carried out to obtain two features of 1×1×C dimensions and then splice them according to channels. Then, the feature is convolved with a 7×7 convolution, and a spatial matrix with the same dimension as the sigmoid activation function obtains the original feature. The new feature after scaling can be obtained by multiplying the spatial attention matrix with the original feature.

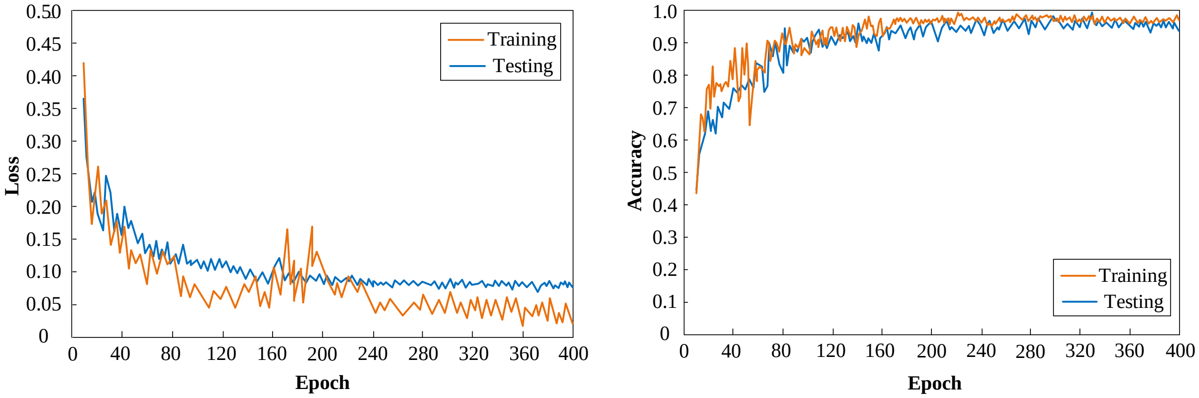
3) Attention fusion: Fig. 4(c) sows the attention fusion module, in which the CBAM module is added after the BN layer of the backbone network. In the training process, the fusion attention module divided the features into G groups according to the channels. After obtaining G from the global average pooling, the features of each group were integrated with the original group features by the site. After the normalization and activation function operation, the features were dotted with the original group features to obtain the activation of significant semantic regions based on the above operations [26]. The upper and lower parts in the figure respectively represent channel attention and spatial attention to features, and the feature W' of a channel or space with different weight distribution can be obtained through the action of the attention module.

IV. Experimental Design and Result Analysis

A. Experimental Environment and Evaluation Indicators

The experimental environment of this work is the Ubuntu 16.04 operating system. The experimental platform is Intel(R)Core I7-7800X processor, six-core 3.5ghz, and NVIDIA GTX1080Ti graphics card. The development language is Python 3.7. The testing platform is Pycharm, and the PyTorch deep learning framework is adopted. Set the initial learning rate as 0.0001, the weight attenuation term as 0.0005, and the random discard rate as 0.5. The batch size is set to 16.

The curves of training and testing performance and iteration times of the model in this paper are represented in Fig. 5. It is evident that as the number of iterations reaches 240, the training and test accuracy rate and Loss curve region are stable, and the model achieves stable convergence.



(a) Loss curve

(b) Accuracy curve

Fig. 5. Curves of the training and testing phases.

Fig. 5 shows the curves during the training and testing stages. (a) Indicates the loss curve. (b) Represents an accuracy curve. Time Overhead (TO) of single image motion recognition, Accuracy, Precision, Recall, F1-score, and other mainstream evaluation indices were employed to assess the model performance in order to confirm the efficacy of the suggested algorithm. Formula (4) to Formula (7) displays the computation expressions. In Table I, the confusion matrix is displayed. In particular, the calculation of Precision and Recall is contradictory, so the precision-recall curve is used for comparison in the current paper. The model's classification performance improves with increasing area under the curve.

$$Accuracy = \frac{Tp + Tn}{Tp + Fp + Tn + Fn} \tag{4}$$

$$Precision = \frac{Tp}{Tp + Fp} \tag{5}$$

$$Recall = \frac{Tp}{Tp + Fn} \tag{6}$$

$$F1 = \frac{2Precision \times Recall}{Precision + Recall} \tag{7}$$

TABLE I. CONFUSION MATRIX CALCULATION

Actual	**Predicted**	
	Positive	***Negative***
Positive	TP	FP
Negative	FN	TN

B. Result Analysis

Fig. 6 shows the confusion matrix generated by this method in three groups of experiments, where the actual action sequence is represented by the rows of the matrix. In contrast, the columns show the action sequence recognized by the algorithm. The confusion matrix states that 307, 311, 301, 318, and 307 times of the six movements were successfully recognized in the three groups of experiments, and the recognition accuracy was 97.07%, 96.14%, 98.34%, 94.03%, and 97.39% respectively. In addition, Fig. 7 represents the average Accuracy, Precision, Recall, and F1 curves of the proposed model in multiple experiments. Also, the performance of the presented model tends to be stable on several experimental results, indicating the robustness of the model presented in the present study.

C. Ablation Experiment

To assess the effect of different components in the model on the overall recognition performance, three ablation experiments were designed, respectively. 1) The original recognition model using skeleton analysis only; 2) Replace original graph convolution with 3D graph convolution; 3) Introduce channel-spatial attention mechanism. Fig. 8 displays the experimental results, where Original represents the first group of experiments; 3D-GC represents that only a three-dimensional graph convolution network is used; ATT means only channel-spatial attention mechanism is used; 3DGC-ATT represents the final model of this paper. It can be seen that compared with experiment 1) of the original control group, the overall performance of the model is improved by 3.91% in recognition accuracy by using 3D graph convolution instead of original graph convolution. The main reason is that the spatial structure features and time features of the skeleton sequence are introduced to improve the expression ability of the action sequence in the skeleton sequence further. In addition, after the introduction of the channel-spatial attention mechanism, the recognition accuracy of the model is improved by 5.18%, which is 1.31% higher than that of the recognition model after the introduction of three-dimensional graph convolution. The reason is that the attention mechanism can focus on the weight distribution of strong features, further, increase the contribution of the largest feature to the overall recognition performance, and suppress the weight of edge features.

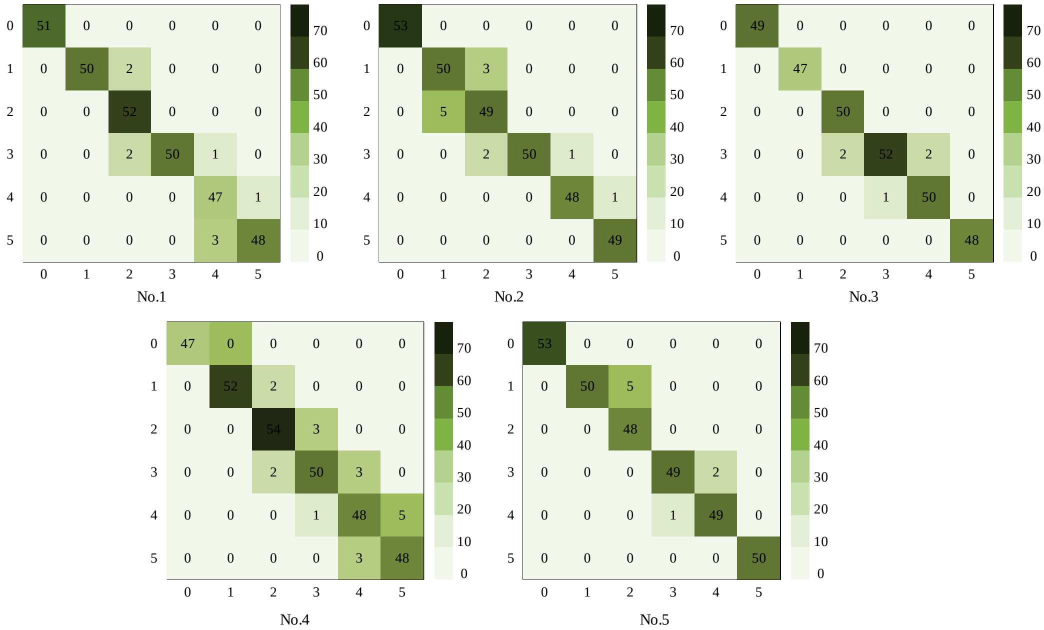


Fig. 6. Confusion matrix.

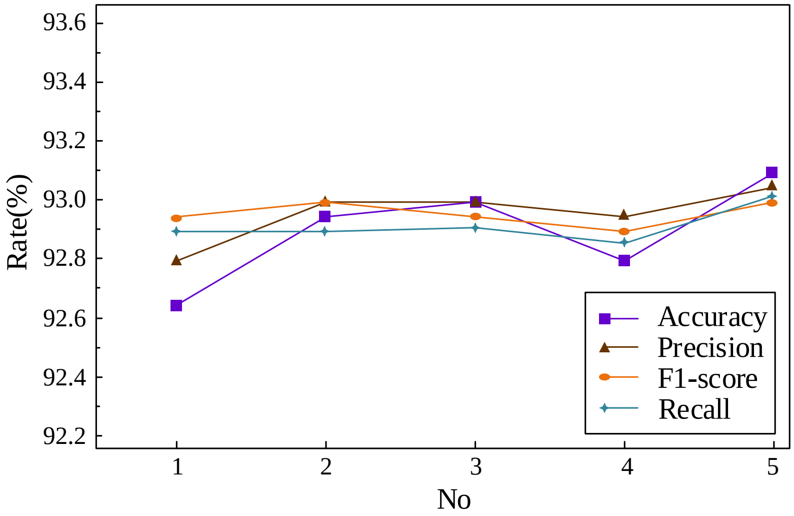


Fig. 7. Curves under different evaluation indexes.

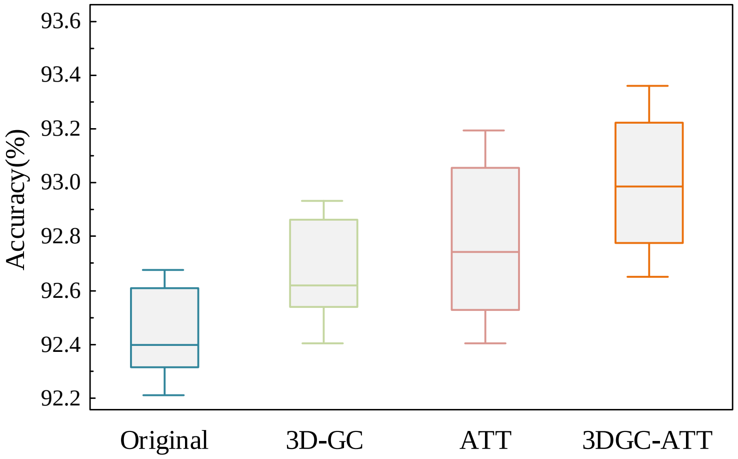


Fig. 8. Ablation experiment.

D. Comparison of Similar Related Works

To verify the effectiveness of the proposed model, the same data set, environment, and evaluation indicators were compared with the current mainstream model. Fig. 9 shows the curves of various models under Accuracy, Precision, Recall, and F1. Fig. 10 shows the comparison results of different models' running times. It can be seen that in Accuracy, Precision, Recall, F1, and other evaluation indicators, the model presented in the present work has obvious competitive advantages compared with mainstream models, and it is also competitive in identifying time costs. Although the time cost is improved compared with the model in literature [27], the comprehensive performance of this model is: The model in this paper performs well. In addition, to integrate the calculation contradiction between Precision and Recall, the precision-recall curve is adopted here for comparison. Fig. 11 shows the comparison results of P-R curves of different models. The model's classification performance improves with the increasing area under the curve.

The P-R curve of the model in this paper can all surround the P-R curve of the comparison model in the basketball action recognition results, which indicates that the performance of the overall action recognition of the model in the current study has been improved to varying degrees after the existing model is improved by using three-dimensional graph convolution and attention mechanism. The above data further verify the robustness of the proposed model.

The basketball training action recognition method based on big data 3D convolution technology is a very promising research direction. The accuracy and efficiency of this method have been validated in many cases, but there are still some areas that need improvement. Especially when dealing with large-scale data, how to improve computational efficiency and reduce the consumption of computing resources is an urgent problem that needs to be solved. In addition, how to improve the generalization ability of the model is also an important research direction. In practical applications, different basketball training scenarios and individual differences among athletes may lead to a decrease in model performance. Therefore, studying how to better adapt the model to these differences is a challenging task. I believe that with the continuous progress of technology and in-depth research, the basketball training action recognition method based on big data 3D convolution technology will be further optimized and improved, and will play a greater role in practical applications.

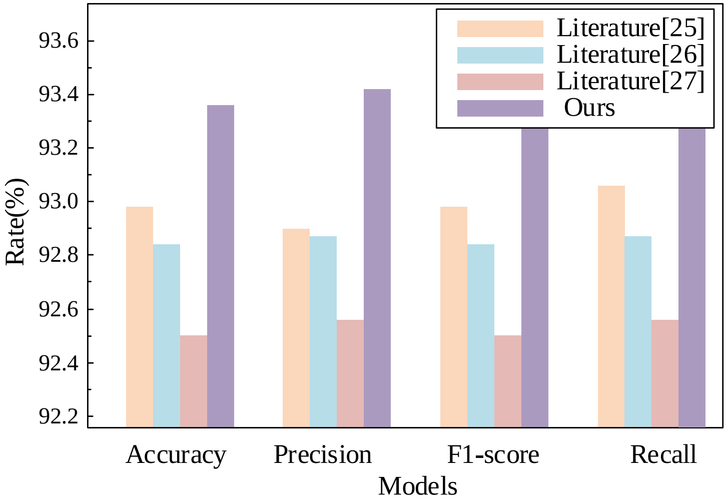


Fig. 9. Performance comparison of different models.

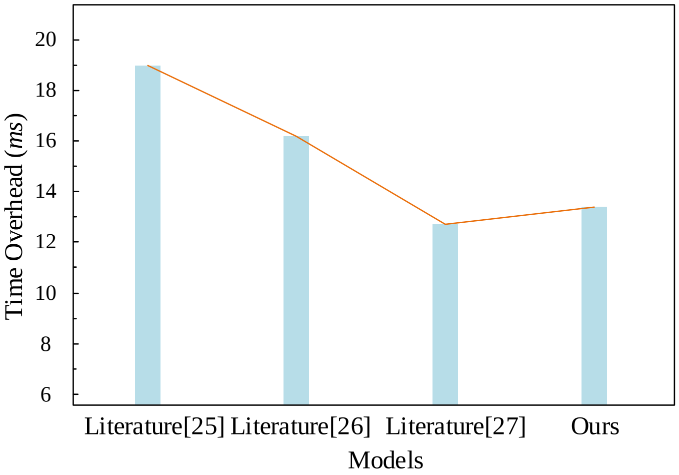


Fig. 10. Comparison of recognition time costs of different models.

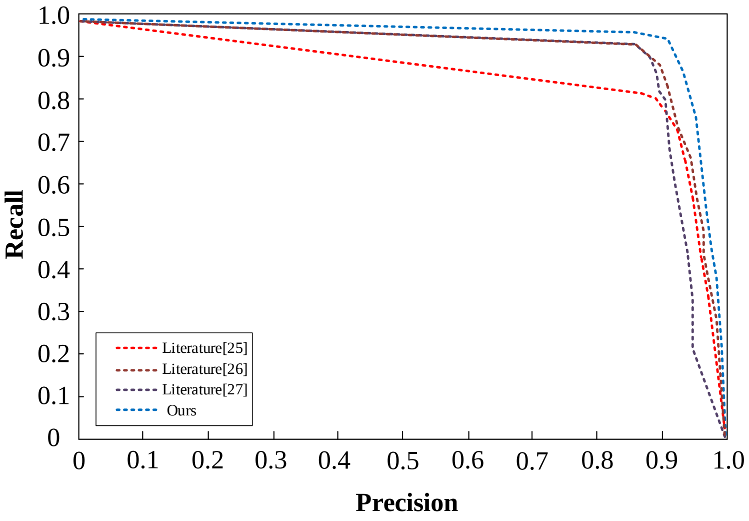


Fig. 11. Comparison of P-R curves of different models.

V. Conclusion

This paper explores the motion capture technology of computer vision and large data sets in advanced training technology application status in the field of motion gesture recognition. Using three-dimensional figure convolution and attention mechanism to improve the existing model, through the test in the practical data, this model is verified in recognition accuracy and time cost is increased. Thus, this model can be applied to the daily training of basketball players and provide a reference for the overall evaluation and decision-making of athletes and coaches.

However, the research has certain limitations. The method based on 3D CNN requires a large amount of computing resources, such as GPU memory and computing power, when processing large-scale basketball training video data. This may result in very time-consuming training and inference processes, which cannot meet the needs of real-time processing. Therefore, how to improve the efficiency of algorithms and the utilization of computing resources is also another challenge faced by current methods.

To address the issues of data scale and quality, future research can explore data augmentation techniques, such as using Generative Adversarial Networks (GANs) to generate high-quality simulated data or using transfer learning methods to acquire knowledge from other relevant datasets. In addition, adaptive learning algorithms can adaptively adjust model parameters based on individual characteristics of different athletes, improving adaptability to individual differences.

Competing of Interests

The authors declare no competing of interests.

Authorship Contribution Statement

Zhen Ni: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Dongsheng Chen: Methodology, Software, Validation.

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Explainable Multistage Ensemble 1D Convolutional Neural Network for Trust Worthy Credit Decision

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***Abstract*—Banking is a dynamic industry that places significant importance on risk management, requiring accurate and interpretable AI models to make transparent lending decisions. This study introduces a groundbreaking approach that combines a multistage ensemble technique with a 1D convolutional neural network (CNN) architecture. The algorithm not only delivers superior classification performance but also offers interpretable explanations for its decisions. The algorithm is designed with multiple strategic steps to enhance model performance without sacrificing explainability. Thorough experiments were conducted using datasets from private banks and non-banking financial companies (NBFCs) in India to evaluate the algorithm's performance. It was compared against various state-of-the-art models, demonstrating remarkable precision, recall, F1 score, and accuracy values of 0.994, 0.992, 0.993, and 0.991, respectively. This outperformed competing models like homogeneous deep ensembles, 1D CNN, and Artificial Neural Networks (ANN). Furthermore, individual borrower dataset evaluations confirmed the proposed algorithm's consistency and efficiency, achieving precision, recall, F1 score, and accuracy values of 0.960, 0.961, 0.952, and 0.964, respectively. The research emphasizes the effectiveness of the explanatory integration decision process, wherein the Explainable Multistage Ensemble 1D CNN not only provides enhanced credit risk prediction but also facilitates transparent and interpretable lending decisions. The algorithm's ability to offer understandable explanations empowers financial institutions to make well-informed lending decisions, reduce credit risk, and foster a more stable and inclusive financial ecosystem.**

Keywords*—Credit risk prediction; explainable AI; multistage ensemble; 1D convolutional neural network; interpretability; transparency; lending decisions; financial institutions

I. INTRODUCTION

In the realm of financial services, credit risk prediction plays a crucial role in enabling sound and responsible lending decisions [1], [2]. Accurate assessments of borrowers' creditworthiness are essential for financial institutions to mitigate risks, ensure fair lending practices, and maintain a stable financial ecosystem. With the advancements in Machine Learning (ML) and artificial intelligence (AI), there has been a surge in the development and adoption of advanced predictive models for credit risk assessment [3], [4]. These models, such as convolutional neural networks (CNNs) and artificial neural networks (ANNs), offer the ability to capture intricate patterns and dependencies within the data, leading to improved predictive accuracy. Despite their impressive performance, the use of complex AI models in the financial industry raises concerns about their inherent opacity and lack of interpretability. Often referred to as "black box" models, these approaches provide little insight into the factors that influence their decisions [5]. In highly regulated and sensitive domains like credit risk assessment, the lack of transparency can be a major obstacle, as stakeholders, including customers, regulators, and internal compliance teams, require explanations to trust and validate the model's decisions [6], [7].

To address these challenges and bridge the gap between predictive accuracy and interpretability, there has been a growing interest in explainable AI (XAI). XAI techniques aim to provide interpretable explanations for complex models, allowing stakeholders to understand how decisions are made and identify the key features driving predictions. In the context of credit risk prediction, XAI offers several advantages, including increased transparency, regulatory compliance, enhanced customer trust, and the ability to detect potential biases in decision-making [8], [9].

In this study, we introduce a technique aiming to incorporate explanations into the decision-making process. Our model utilizes multistage ensemble techniques, known for enhancing interpretability by offering explanations at various decision stages. By combining the strengths of multiple models, this ensemble approach improves predictive accuracy while retaining the capability to provide meaningful explanations for credit risk evaluations.

The proposed model’s objective is to achieve high predictive accuracy while ensuring that the underlying decision process is transparent and understandable. By providing interpretable explanations, financial institutions can gain valuable insights into the model's risk assessments, understand the relative importance of different features, and detect potential biases, ultimately leading to more informed lending decisions.

To proposed Explainable Multistage Ensemble 1D CNN model, is evaluated for the effectiveness on two different data sets. We conducted comprehensive experiments on enterprise credit risk dataset and individual borrower credit dataset. We compared the performance of proposed model with other state-of-the-art approaches, including Homogeneous deep Ensembles (ANN and CNN), as well as standalone ANN and 1D CNN classifiers. The results demonstrate the superior predictive accuracy and interpretability of our proposed model, reinforcing its potential value in the domain of credit risk prediction.

The rest of this paper is structured as follows: In Section II, covers a comprehensive review of related studies in the fields of credit risk prediction, explainable AI, and ensemble techniques. Section III presents the methodology and architecture of our innovative model. Following that, in Section IV, we present and analyze the experimental results, highlighting the strengths of our approach compared to other existing methods. Finally, in Section V, we conclude the paper and discuss potential avenues for future research.

II. Literature Review

Assessing credit risk is a crucial undertaking in the financial sector, as it involves evaluating borrowers' creditworthiness to make well-informed lending choices. To develop predictive models for credit risk assessment, researchers have explored various AI and machine learning approaches over time. Furthermore, the growing need for transparency and interpretability in models has given rise to explainable AI (XAI) techniques, which aim to provide insights into the decision-making process of intricate models. In this section, we present a thorough examination of pertinent literature concerning credit risk prediction, explainable AI, and ensemble techniques.

A. Credit Risk Prediction

The literature on credit risk prediction is vast and diverse, with numerous studies focusing on developing accurate and reliable models. Traditional credit scoring methods, such as logistic regression and decision trees, have long been used in the industry. However, with advancements in machine learning, more sophisticated models, including neural networks, support vector machines (SVM), and gradient boosting algorithms, have gained popularity due to their ability to capture complex patterns in credit data [4], [10], [11], [12].

B. Explainable AI for Credit Risk Prediction

The need for model transparency and interpretability in credit risk prediction has led to the exploration of explainable AI techniques. Several studies have proposed methods to generate explanations for credit risk models, enabling stakeholders to understand the rationale behind model decisions. Approaches such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) have been applied to credit risk models to provide local and global interpretations [9], [13], [14]. Additionally, rule-based models and decision trees have been used as interpretable alternatives to black box models [15], [16].

C. Ensemble Techniques

Ensemble methods have demonstrated remarkable success in various machine learning tasks, including credit risk prediction. Ensemble approaches combine the predictions of multiple models to improve overall performance and robustness. Bagging and boosting techniques, such as Random Forest and Gradient Boosting Machines (GBM), have been widely employed in credit risk prediction [17]. Recent research has explored the benefits of using homogeneous and heterogeneous ensembles, where models from the same or different algorithm families are combined [8], [18], [19], [20], [21]. Researchers from various domains proved the effectiveness of ensemble techniques in their fields [22], [23], [24], [25], [26], [27], [28], [29], [30].

D. Multistage Ensemble Techniques

Multistage ensemble techniques offer a promising approach for improving both predictive accuracy and model interpretability. By combining multiple models at different stages of the decision-making process, these methods can provide valuable insights into the model's reasoning. Various studies have shown that multistage ensembles can outperform single model [22], [25], [30]. However, the application of multistage ensemble techniques in credit risk prediction remains relatively unexplored.

Credit risk prediction is a critical domain where model accuracy, transparency, and interpretability are of utmost importance. While various AI models have been employed for credit risk assessment, the emergence of explainable AI and ensemble techniques presents new opportunities to enhance predictive performance and provide interpretable explanations for model decisions. The proposed approach aims to leverage explainable multistage ensemble techniques to address the dual objectives of predictive accuracy and model transparency.

III. Proposed Methodology

A. Credit Risk Dataset used in the Experiments

The analysis focuses on two distinct borrower segments: individual borrowers and enterprise borrowers. Individual borrowers obtain loans in their personal capacity, while enterprise borrowers secure loans on behalf of their businesses. Data for both segments were collected under a Non-Disclosure Agreement (NDA). The individual borrower dataset was obtained from a private bank in India and comprises 105,163 records, with 100,497 records (95.6%) falling into the negative class (non-risky) and 4,665 records (4.4%) classified as positive class (risky). The enterprise dataset was collected from an NBFC (Enterprise) in India and consists of 97,451 records, with 92,900 classified (95.3%) as the negative class and 4,550 (4.7) as the positive class. The sample description is presented in Fig. 1. The target variable in this analysis is "risk," which is binary, and the other variables serve as independent variables. The dataset contains a mix of categorical and numerical variables. All data used in this analysis were collected following ethical guidelines and legal agreements to ensure confidentiality and privacy.

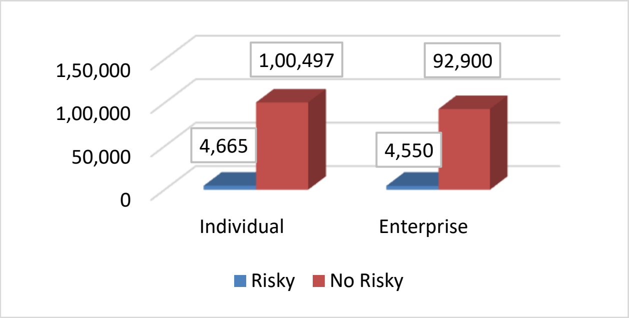

Fig. 1. Sample profile.

B. Multistage Ensemble Architecture Overview

The multistage ensemble classifier is designed to improve classification performance by employing a series of stages, each containing a 1D Convolutional Neural Network (CNN). Unlike a single CNN model, the ensemble classifier combines the outputs of all stages to make the final prediction. Each stage contributes its specialized knowledge to enhance the overall decision-making process. The choice of the number of stages will depend on the complexity of the classification task, the size of the dataset, and the available computational resources. Determining the appropriate number of stages for the ensemble classifier is crucial. Too few stages might limit the model's representational power, while too many stages could lead to excessive computational requirements and potential overfitting. The optimal number of stages is typically determined through experimentation and performance evaluation on the validation set. In the proposed setup five stages are used.

C. Stage-wise CNN Architecture

For each stage, design a 1D CNN architecture tailored to the specific characteristics of the dataset and classification problem. Each stage's CNN should consist of multiple convolutional layers, followed by activation functions and pooling layers. This design enables the CNN to learn hierarchical features from the 1D input data. Experimentation is done with different filter sizes, strides, and the number of filters in each layer to identify the configuration that yields the best results. Additionally, techniques like batch normalization are applied to accelerate training and improve convergence. To reduce overfitting, introduced dropout layers, which randomly deactivate neurons during training, preventing reliance on any single set of features. Table I represents the architecture of a 1D CNN-based ensemble classifier with multiple stages, where each stage consists of Conv1D layers, Batch Normalization, Max Pooling, LeakyReLU activation, and finally, an Average Pooling, Dropout, and Dense layer for classification.

D. Conv1D Layer

This layer performs 1-dimensional convolution on the input data. The "Filters" parameter is set to 128 for the first Conv1D layer, 256 for the second and third Conv1D layers, and 512 for the fourth Conv1D layer. The number of filters determines the number of features maps the layer will learn. Higher filter values allow the model to learn more complex patterns but also increase computational complexity.

E. Batch Normalization Layer

Batch normalization normalizes the input of the layer, helping to stabilize and accelerate the training process. It improves convergence and prevents internal covariate shift, which occurs when the distribution of inputs to a layer change during training.

F. Max Pooling 1D Layer

Spatial dimensions of the data can be reduced by using max pooling while retaining the most important features. The "Pool size" parameter is set to 4 for all Max Pooling layers. This means the layer will take the maximum value within a sliding window of size 4 along the temporal dimension.

TABLE I. ARCHITECTURE OF A 1D CNN-BASED ENSEMBLE CLASSIFIER WITH MULTIPLE STAGES

Type of Layer	Other Parameters
Conv1D **Batch Normalization** **Max Pooling 1D** **Activation**	Filters = 128 - Pool size = 4 LeakyReLU activation
Conv1D **Batch Normalization** **Max Pooling 1D** **Activation**	Filters = 256 - Pool size = 4 LeakyReLU activation
Conv1D **Batch Normalization** **Max Pooling 1D** **Activation**	Filters = 256 - Pool size = 4 LeakyReLU activation
Conv1D **Batch Normalization** **Max Pooling 1D** **Activation**	Filters = 512 - Pool size = 4 LeakyReLU activation
Average Pooling 1D **Flatten** **Dropout** **Dense**	Pool size = 2 - Rate 0.4 Regularizer L2 (0.001), Softmax activation

G. LeakyReLU Activation

Leaky ReLU (Rectified Linear Unit) is an activation function that introduces a small negative slope for negative input values, preventing the "dying ReLU" problem. The negative slope helps the model during backpropagation even for negative inputs, leading to improved gradient flow and avoiding potential dead neurons.

H. Average Pooling 1D Layer

After the last Conv1D layer, an Average Pooling layer is used instead of Max Pooling. Average pooling computes the average value of each feature map, reducing the data dimensionality and providing a global summary of the features.

I. Flatten Layer

The Flatten layer converts the 3-dimensional output from the previous layers into a 1-dimensional vector, preparing it for the fully connected layers.

J. Dropout Layer

Dropout is a technique that randomly drops out (sets to zero) a fraction of the neurons during training. The "Rate" parameter is set to 0.4, meaning 40% of the neurons will be dropped out during training. This helps prevent overfitting and encourages the model to learn more robust representations.

K. Dense Layer

The Dense layer is a fully connected layer, linking each neuron from the preceding layer to every neuron in this current layer. With a "Pool size" parameter of 2, this layer comprises 2 output neurons. To prevent overfitting, the layer employs L2 regularization with a coefficient of 0.001, penalizing large weights. By using the Softmax activation function, the final output values are transformed into probability scores for each class, making it suitable for multi-class classification.

L. Training the Stage-wise CNNs and Ensemble Combination

In the proposed approach, we utilize a multi-stage Convolutional Neural Network (CNN) architecture, where each stage's CNN is trained independently on the training set. Throughout the training process, we closely monitor the model's performance on the validation set to prevent overfitting. To achieve optimal results, we tune hyperparameters like learning rate, batch size, and the number of epochs. After training all stages' CNNs, we proceed to combine their outputs to create the final prediction. To evaluate the effectiveness of our ensemble classifier, we employ the test set and calculate various standard metrics, including accuracy, precision, recall, F1-score, and confusion matrices. Subsequently, we conduct a comparative analysis to assess how our proposed ensemble classifier performs in comparison to other state-of-the-art techniques. By doing so, we aim to demonstrate the superiority of our approach in making accurate predictions.

M. Explanation Generation

Adaptive Relevance Scaling for Layer-wise Relevance Propagation (ARSLRP) based explanations are employed to interpret the decision-making process of the multistage 1D CNN based ensemble classifier. Its primary objective is to attribute the model's prediction to the input features, offering a human-understandable explanation for the decision outcomes. ARSLRP operates on the principle of redistributing the model's output back to its input features, layer by layer, to identify the most influential features contributing to the final prediction.

The ARSLRP process starts from the final layer of the network, where the relevance is initialized based on the model's output (e.g., for a classification problem, relevance is initialized for the predicted class). Then, the relevance is propagated backward through the network layers using the Alpha-Beta rule until it reaches the input layer. The relevance scores obtained after the ARSLRP process indicate the importance of each input feature in influencing the model's decision.

IV. Results and Discussion

Multi Stage Heterogeneous Ensemble 1D CNN The proposed multistage ensemble 1D CNN model is evaluated based on various performance matrices namely precision, recall, f1-score and accuracy on two datasets namely enterprise data set and individual dataset. Table II illustrates the results for various performance matrices on enterprise dataset.

TABLE II. Explainable Ensemble 1 D CNN Performance on NBFC Data

Algorithm	Precision	Recall	F1-score	Accuracy
Proposed Algorithm (Multistage 1 D CNN)	0.994	0.992	0.993	0.991
Homogeneous deep Ensemble (ANN)	0.910	0.950	0.930	0.950
Homogeneous deep Ensemble (CNN)	0.900	0.950	0.930	0.950
ANN	0.891	0.893	0.892	0.894
1 D CNN	0.893	0.891	0.894	0.892

1) Precision: Multistage 1D CNN model achieves a precision of 0.994. This means that when the model predicts a customer as being at risk of defaulting on their credit, it is correct 99.4% of the time. A high precision value indicates that the model is effective in minimizing false positives, i.e., it rarely misclassifies customers who are not likely to default as high-risk, which is essential for banks to avoid unnecessary precautionary measures for low-risk customers.

2) Recall: The Multistage 1D CNN model achieves a recall of 0.992, meaning it successfully captures 99.2% of the customers who are genuinely at risk of defaulting on their credit. A high recall value indicates that the model has a low false negative rate, meaning it rarely misses identifying customers who are actually high-risk. This is crucial for banks to ensure that they do not overlook customers who pose a real credit risk.

3) F1-score: For the Multistage 1D CNN model, the F1-score is 0.993, which indicates an excellent balance between precision and recall. It demonstrates that the model is effective in achieving both accurate positive predictions and comprehensive identification of high-risk customers. A high F1-score suggests that the model is well-suited for credit risk prediction tasks where precision and recall need to be balanced.

4) Accuracy: The Multistage 1D CNN model achieves an accuracy of 0.991, which means it correctly predicts approximately 99.1% of all instances in the dataset. This high accuracy indicates that the model performs exceptionally well in making overall accurate predictions, regardless of the class distribution. A high accuracy value shows the reliability and effectiveness of the model in capturing credit risk patterns and making informed decisions.

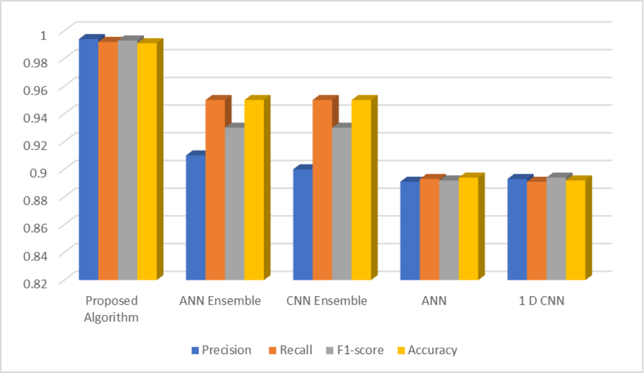

Fig. 2. Performance of proposed algorithm on NBFC dataset.

In summary, the results for the Multistage 1D CNN model in credit risk prediction are highly impressive. The model achieves exceptional precision, recall, F1-score, and accuracy values, demonstrating its ability to identify high-risk customers accurately while minimizing false predictions. This performance surpasses that of other algorithms tested in the study, making the Multistage 1D CNN model a promising choice for credit risk assessment tasks, and suggesting its potential for real-world implementation in financial institutions to enhance credit risk management and decision-making processes. Pictorial illustration for the same is shown in Fig. 2.

Similarly, Table III presents the performance metrics of various algorithms for individual borrower credit risk prediction dataset, with each row corresponding to a specific model. Among the algorithms tested, the "Proposed Algorithm" based on the Multistage 1D CNN stands out as the top-performing model across multiple evaluation metrics.

The Proposed Algorithm achieves a precision of 0.960, indicating that 96% of the predicted high-risk customers are genuinely at risk of defaulting on their credit. This demonstrates the model's effectiveness in minimizing false positives, ensuring that it correctly identifies most customers who pose an actual credit risk. Furthermore, the Recall for the Proposed Algorithm is 0.961, signifying that the model captures 96.1% of the actual high-risk customers present in the dataset. A high recall score suggests that the model has a low false negative rate, meaning it rarely misses identifying customers who are truly at risk of defaulting on their credit. This capability is crucial for financial institutions to avoid overlooking potential credit risks. The F1-score of 0.952 for the Proposed Algorithm reflects a balance between precision and recall, indicating a good overall performance. The F1-score is particularly valuable when there is an uneven distribution of classes in the dataset, making it a reliable measure for credit risk prediction tasks.

Lastly, the Proposed Algorithm achieves an accuracy of 0.964, implying that it makes accurate predictions for approximately 96.4% of all instances in the dataset. A high accuracy value indicates that the model's overall performance is strong, making it a reliable tool for credit risk assessment. In comparison, the other algorithms, including Homogeneous deep Ensemble (ANN), Homogeneous deep Ensemble (CNN), ANN, and 1D CNN, also show respectable results, but the Proposed Algorithm based on the Multistage 1D CNN consistently outperforms them across all metrics. In conclusion, the results demonstrate that the Multistage 1D CNN model proposed in the study is highly effective for credit risk prediction. Its balanced precision, recall, and F1-score, combined with its impressive accuracy, make it a promising approach for financial institutions seeking accurate and reliable credit risk assessment models. Pictorial illustration for the same is shown in Fig. 3.

B. Explanations / Interpretations

In this study, we explored the ARSLRP as an explainability technique for credit risk prediction models. The goal was to gain insights into how the model makes predictions and to provide transparent explanations to stakeholders, such as regulators, auditors, and customers, who need to understand the factors contributing to credit risk assessments. Fig. 4 and Fig. 5 illustrate the results generated by the model to provide explanations on enterprise and individual borrower dataset respectively.

TABLE III. EXPLAINABLE ENSEMBLE 1 D CNN ON INDIVIDUAL BORROWER DATASET

Algorithm	**Precision**	**Recall**	**F1-score**	**Accuracy**
Proposed Algorithm (Multistage 1 D CNN)	0.960	0.961	0.952	0.964
Homogeneous deep Ensemble(ANN)	0.918	0.952	0.939	0.958
Homogeneous deep Ensemble(CNN)	0.950	0.958	0.940	0.959
ANN	0.881	0.883	0.882	0.884
1 D CNN	0.883	0.881	0.884	0.882

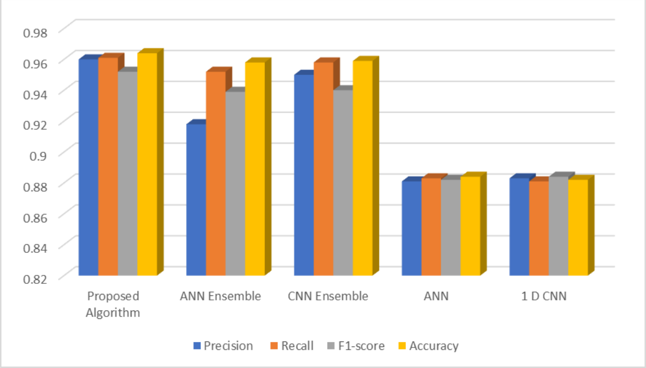

Fig. 3. Performance of proposed algorithm on individual borrower dataset.

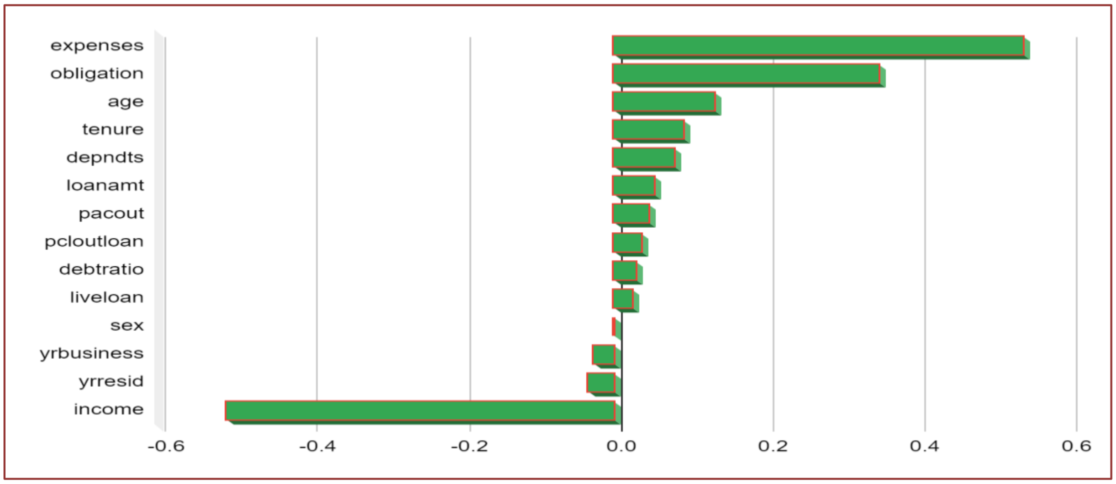

Fig. 4. Explanations / Interpretations on NBFC dataset.

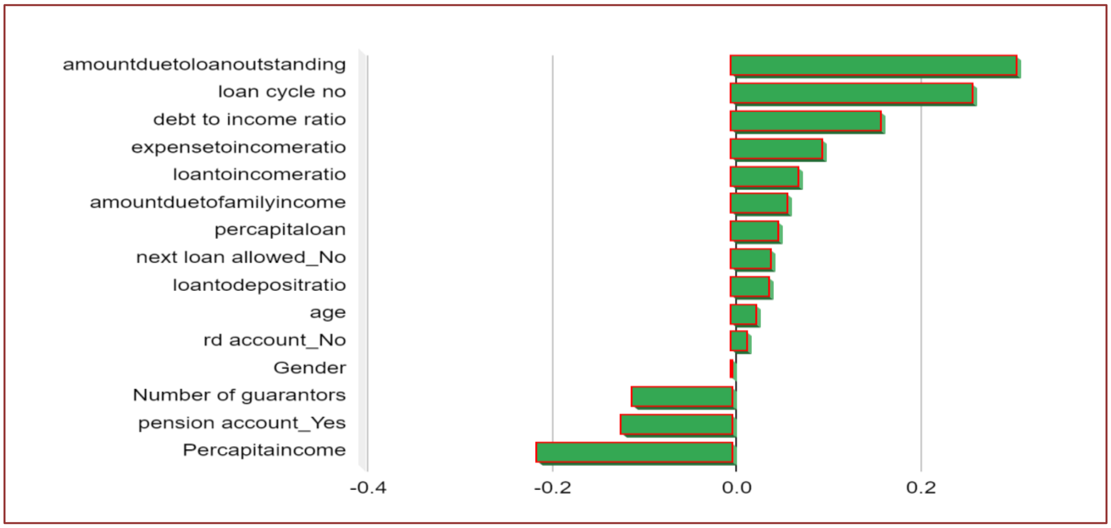

Fig. 5. Explanations / Interpretations on individual borrower dataset.

Fig. 4 illustrates the results generated by the model to provide explanations on enterprise (NBFC) dataset. The ARSLRP values for the NBFC dataset reveal key insights into the factors influencing the model's risk predictions. Notably, "Expenses" stands out as the most impactful variable with a substantial positive ARSLRP value of +0.5397. This implies that clients with higher reported family expenses are deemed riskier by the model. It suggests a correlation between increased spending and elevated risk in the context of the NBFC dataset. Similarly, "Obligation" contributes positively with an ARSLRP value of +0.3480, suggesting that clients with higher financial obligations are also considered riskier. These findings underscore the model's sensitivity to financial commitments and their association with increased risk. The positive contributions of demographic factors come into play with variables such as "Age" (+0.1320) and "Tenure" (+0.0915). The positive ARSLRP values indicate that older clients are perceived as riskier. Entrepreneurs with increased age may have higher family and social commitments as well as more expenses towards business and family. This could suggest that the model associates increased age and tenure with a higher likelihood of risk in the context of the dataset. The presence of dependents ("Dependents" with +0.0778) and certain loan-related variables, such as "Loan Amount" (+0.0521) and "Payout" (+0.0443), also contribute positively, indicating that clients with larger loan amounts, more dependents, and higher payouts are associated with increased risk according to the model. These associations in general reflect the model's perception of increased financial commitments and complexities contributing to higher default risk.

The variable "Sex" has a neutral impact with an ARSLRP value of 0.0000, suggesting that gender does not significantly contribute to the model's risk predictions. This implies that the model does not distinguish between male and female clients when assessing risk. On the negative side, variables such as "Year in Business" (-0.0258), "Year at Residency" (-0.0350), and "Income" (-0.5101) exert a negative influence on risk predictions. Longer durations in business and residency are associated with decreased risk, suggesting that recent businesses and residents are considered riskier by the model. The most impactful negative contributor, "Income," indicates that clients with higher incomes are perceived as less risky.

Fig. 5 illustrates the results generated by the model to provide explanations on individual borrower dataset. The ARSLRP values offer a comprehensive understanding of the factors influencing risk predictions in the individual borrower dataset. Starting with positive contributors, "Amount Due to Loan Outstanding" is the most influential variable with a positive ARSLRP value of +0.3076. This suggests that borrowers with higher number of dues of the loan outstanding are perceived as riskier by the model. Similarly, "Loan Cycle Number" and "Debt to Income Ratio" contribute positively, indicating that borrowers with higher loan cycles and those with elevated debt relative to income are associated with increased risk. These findings emphasize the model's sensitivity to the financial positions and credit history of the borrowers.

Additionally, various financial ratios such as "Expense to Income Ratio," "Loan to Income Ratio," and "Loan to Deposit Ratio" contribute positively, indicating that borrowers with higher expense and loan-to-deposit ratios are perceived as riskier. The model seems to prioritize a cautious approach towards borrowers with higher financial commitments and dependency on loans. The positive contribution of "Age" suggests that older borrowers are associated with increased risk, possibly indicating that the model considers factors related to the borrower's life stage in its risk assessment. The middle age borrowers may have higher family commitments towards children education, health and housing requirements which pushes them to higher level of debt.

Conversely, the neutral contribution of "Gender" suggests that gender does not significantly influence the model's risk predictions. The model does not differentiate between male and female borrowers in terms of perceived risk. Moving to negative contributors, "Number of Guarantors" negatively influences risk predictions, implying that borrowers with more guarantors are considered less risky. This suggests that having additional guarantors provides a sense of security in the model's assessment. The negative impact of "Pension Account (Yes)" as a contributor indicates that borrowers with pension

accounts are considered less risky. This aligns with the notion that individuals with stable sources of income, such as a pension, may be perceived as more reliable borrowers. However, the most impactful negative contributor is "Per Capita Income" with a negative ARSLRP value of -0.2108. This implies that borrowers with increasing per capita income are seen as less risky by the model. It suggests that higher individual income levels play a significant role in mitigating perceived risk of defaults.

ARSLRP values in individual borrower dataset reveal that the model relies on a combination of financial ratios, historical borrowing patterns, and demographic factors to assess default risk. Positive contributors highlight the risk associated with higher outstanding amounts, specific financial ratios, and certain borrower characteristics. Negative contributors point to factors such as having more guarantors, possessing a pension account, and higher per capita income as indicators of lower perceived risk. These insights provide valuable guidance for refining risk assessment strategies and making informed decisions tailored to the nuances of individual borrower datasets.

The ARSLRP -based explanations can shed light on the model's decision-making process and highlight the features that are most influential in determining credit risk. Our findings indicate that ARSLRP provides meaningful and interpretable explanations for credit risk predictions. By propagating relevance through each layer of the model, we identified the features that contribute the most to the final prediction. This feature importance helps users comprehend the risk factors considered by the model, leading to enhanced transparency and trust in the credit risk assessment process. Moreover, ARSLRP enables us to analyze how the model handles both positive and negative instances. We observed that high-risk customers received higher relevance on features associated with past credit history, debt-to-income ratio, and payment delinquencies. On the other hand, low-risk customers obtained higher relevance on features like steady income, low credit utilization, and a history of timely payments. These findings align with domain knowledge and provide valuable insights for risk managers in understanding the decision-making process of the model.

Furthermore, the ARSLRP -based explanations revealed cases where the model's predictions deviated from conventional wisdom. In such instances, stakeholders can closely investigate the underlying factors and potentially identify areas for model improvement or data validation. For instance, if the model assigns high relevance to a seemingly irrelevant feature, such as a customer's occupation, it may raise concerns about data quality or the model's sensitivity to certain attributes. One of the strengths of ARSLRP is its ability to handle complex models, including deep learning architectures. Traditional linear models or decision trees often lack the capacity to capture intricate patterns in credit risk prediction, whereas deep learning models like CNNs and LSTMs can capture nonlinear relationships in the data. ARSLRP can handle such complex architectures, providing detailed explanations for individual predictions and overall model behavior. In conclusion, ARSLRP -based explanations offer a valuable tool for interpreting credit risk prediction models. The insights provided by ARSLRP facilitate understanding model predictions, identifying influential features, and assessing the model's performance.

V. Conclusion

Credit risk prediction is a vital aspect of the financial industry, where accurate assessments of borrowers' creditworthiness are crucial for making responsible lending decisions. This research explored the integration of explainable AI (XAI) techniques and ensemble methods to address the dual objectives of predictive accuracy and model interpretability in credit risk prediction. Specifically, the proposed approach leverages multistage ensemble techniques with a 1D CNN architecture to achieve both high performance and transparent decision-making. Our proposed approach aims to enhance credit risk prediction by integrating multistage ensemble techniques with a 1D CNN architecture. The model operates through multiple stages, providing interpretable explanations for its decisions, while maintaining high predictive performance. By offering transparency into the decision-making process, our proposed approach empowers financial institutions to understand and validate the model's risk assessments, ensuring fair lending practices and regulatory compliance. In conclusion, the proposed approach presents a novel contribution to the field of credit risk prediction. By combining the advantages of multistage ensemble techniques and XAI, our proposed model offers a balance between predictive accuracy and model interpretability, making it a valuable tool for credit risk assessment in the financial industry. Transferability of the trained model across two credit risk domains or financial institutions is investigated, assessing the model's generalizability and ability to provide meaningful explanations in diverse settings. As a future enhancement extend the model to handle time-series or sequential data that often appear in credit risk scenarios. Incorporating temporal dependencies and sequential patterns could enhance the model's predictive performance and provide more meaningful explanations.

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A New Weighted Ensemble Model to Improve the Performance of Software Project Failure Prediction

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***Abstract*—The development of a software project is frequently influenced by various risk factors that can lead to project failure. Predicting potential software project failures early can aid organizations in making decisions regarding possible solutions and improvements. This paper proposes a software project failure prediction model based on a weighted ensemble learning approach. The proposed model aims to determine the failure probability as well as the expected project outcome (Success/Failure). Various ensemble approaches, such as simple majority voting, can be employed in predicting software project failure. However, in majority voting algorithms, all base models have the same weights, resulting in an equal effect on the final prediction result, regardless of their predictive abilities. Our proposed algorithm assigns higher weights to base models that demonstrate a greater ability to correctly predict more challenging data instances. The proposed model is developed based on a dataset gathered from real previous software project reports, comprising both successful and failed projects, to provide evidence supporting the predictive model's capabilities and to obtain high-confidence results. The performance of the developed model is comprehensively assessed through various measures, revealing its superiority in predicting software project failures compared to both simple majority voting and individual models. This research suggests that the proposed model can be integrated into the software system development process, spanning requirement analysis, planning, design, and implementation phases, to evaluate the project's status and identify potential risks.**

Keywords*—Ensemble learning; failure prediction; base models; project outcome

I. Introduction

Assessing the probable software project failure early during development process can mitigate the effect of the undesirable events that could lead to project failure [10]. The paper aims to develop new weighted ensemble predictive model which use historical failure data gathered from several past software projects to accurately predicting possible failures in future software projects. The developed model can be used early in the system software engineering process at inception and planning phase when decisions are being made to specify the projects to be embarked upon in the project portfolio. Furthermore, this model can be used during any phase of software development process to avoid project failure and improve reliability.

Ensemble learning is selected because it has been observed that this method achieves better results in terms of diversity and accuracy [1]. Using ensemble methods improve prediction results by combining abilities of different single predictors into one prediction model [7]. As these single predictors differ in the approach used, parameters, and dealing with training data, combining prediction abilities of these predictors enable the ensemble algorithms to capture different characteristics of the training data and produce more reliable and accurate prediction [7].

Ensemble learning is a machine learning technique where multiple base models are combined to produce one optimal model ([3]; [4]). The ensemble model constructs a set of base models on training data and then combines them or selects the best one to use [11]. The objective of this technique is to improve the model predictive accuracy over traditional single component models [18]. In many cases, the ensemble predictors show higher performance than other individual prediction models [1], [7]. According to [7], there are three reasons why this technique can improve the prediction accuracy:

1) The single component models learn from training data to perform prediction of the new examples. However, it can be hard to perform accurate prediction when the amount of training data is small. This problem can be solved by constructing a set of base models (combined to one ensemble model) and find the optimal prediction result.

2) Several prediction techniques use local search approaches such as gradient decent to find the optimal class. Even if the available training data is enough, these searches can stick to a local optimum. Since finding the global optimum can be computationally expensive, ensemble classifiers perform multiple local searches started at different data points to find the optimal class.

3) In such situations, it can be hard to find the optimal solution in the search space of the single classifiers. A combination of multiple classifiers could approximate the optimal solutions than the separated single classifiers. An example of a two-class classification problem is shown in Fig.1. In this example, none of the three classifiers A, B, and C can separate the two classes (+ and −) perfectly. The ensemble classifier as illustrated by a bold line in Fig. 1, that

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combines the three single classifiers is capable of classifying the two classes accurately.

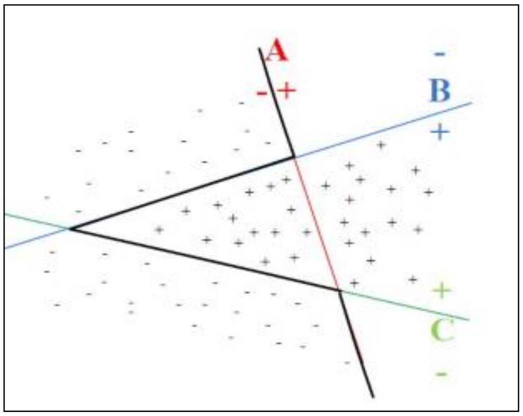

Fig. 1. Example of the three classifiers.

Although these reasons show that the ensemble classifiers could perform better than single classifiers, ensemble learning needs enough diversity to obtain accurate results [13]. This means that the classifiers should produce different errors in order to be able to learn from each other. When the classifiers make nearly the same errors, they will behave like a single classifier.

In this paper, a new weighted ensemble prediction model is proposed to predict the software project failure. This model combines ensemble-learning prediction with the predictor selection approach. The proposed algorithm incorporates six base models, namely, neural networks (NNs), logistic regression (LR), support vector machine (SVM), naïve Bayes (NB), adaptive neurofuzzy inference system (ANFIS), and decision trees (DT). These methods are selected because they show adequate prediction performance according to the study conducted by Ibraigheeth and Eid [9]. We suggest that the different prediction abilities of these six methods enable the proposed algorithm to capture different characteristics of the training data and produce more reliable and accurate prediction.

The proposed algorithm assigns a unique “ranking number” to each base model according to its ability to predict the most difficult-to-predict data. A higher performance model on the difficult-to-predict data will be assigned higher ranking numbers. A normalize weighted vector is constructed based on these ranking numbers, and the final probability of failure result is obtained based on the weight assigned for each base model.

In the proposed method, when the base models are constructed, a unique “ranking number” is assigned to each one according to its performance result over the data subset with lower average performance result, which was the most difficult subset to predict. The algorithm constructs a performance vector for each base model over all data subsets. In addition, the approach constructs a vector that represents the average performance results over each data subset for all base models. Furthermore, a ranking vector for base models is constructed as well as a normalized weight vector, which represents the weights of the base models.

II. RELATED WORKS

Over the past years, many ensemble approaches have been proposed. According to [5], ensemble methods can be categorized into two types: homogeneous and heterogeneous ensembles. In the homogeneous ensemble, the same learning algorithm using different training subsets trains a set of individual models. The final decision is taken by combining the outputs of these models. Examples of such ensemble methods in the literature include bagging [15], AdaBoost [37], and Random Forest [16]. In the heterogeneous ensemble, different learning algorithms using the same training set generate different models. The heterogeneous ensemble learning emphasizes more on meta-data combination techniques ([17]; [26-30]) to achieve a higher performance than an individual model. Wang and Zhong [33] applied the information granularity approach to develop an ensemble system combining multiple classifiers. First, the weighted distances between granularity prototypes and the base classifiers outputs are observed. Then, the shortest distance prototype is selected to predict the class label. Wu [35] proposed a new weighted ensemble method that considers the performance information for the base models in previous literature to obtain their optimal weights. Blaser and Fryzlewicz [22] developed a new ensemble system that generates the base models after generating matrices to rotate the features space. Moreover, different learning methods were applied for many ensemble systems, such as supervised learning [39], incremental learning ([2], [14], [36]) and multilabel classifiers ([12], [21]). Several researches focused on enhancing the performance of the existing ensemble approaches. Several methods were applied for this purpose, e.g., clustering approach [24], dynamic classifiers selection [23], and hybrid methods used in a random subspace to assign weights for the base classifiers [40]. Hybrid ensemble, which combines sample and feature space-based learning was proposed in [38]. Several techniques have been proposed to enhance AdaBoost performance, for example, by applying linear programming to maximize the margin between different classes and training instances [20].

Even though there are many researches concentrate on addressing software project failures [8], [31], [32], [41], most of these researches don’t perform project failure prediction. Ewusi-Mensah [8] was aimed to identify the impact of different failure factors on the SDLC stages. The empirically based study defines the reasons behind these factors and how they can prevented. Takagi et al. [31] performed a questionnaire based approach in order to determine core risk factors. A logistic regression model is used to characterize the confused projects, and to predict if the software project is risky or not risky. However, the developed model does not predict failures. Verner et al. [32] investigated number of failed projects to determine the factors behind project failing. This research aimed only to identify failure factors, and it did not predict the project failures. Rayes et al. [25] also propose an effective project resources allocation to maximize the probability of the project success. The authors suggest a strategy for effective resources allocation to get high success rate with minimum cost. The developed model was to identify and control the risks that affect the project success. However, the failure prediction is not observed also in this research.

Wang et al. [34] developed a predictive model based on Bayesian Network in order to predict the software projects outcome through prediction and controlling the variance in estimated project schedule. This research aimed to maximize the opportunity to complete the project on time through project re-planning, resource re-allocation, and schedule variance factors identification. Therefore, no software failure prediction is performed in this research. Lehtinen et al. [19] performed analysis in corporation with four software organizations to recognize the reasons behind failures and the relations among them. Their research developed diagrams that describe causal relationships among failure causes, and they recommended performing specific analysis for each cause, and managing these causes outside the development area to prevent the software project failure. However, a limitation of this research is the limited number of failure analyzed cases.

Most of previously developed methods were applied on certain case studies. Consequently, those methods might not be applicable for other software projects. Furthermore, many of these methods were implemented to assess the failure through specific phase of software development process. In this context, one of main contributions of our research is developing a new prediction model that can be applied on any software project during any phase of software development process.

III. Methodology

In the initial phase of this study, careful consideration is given to the selection of model inputs, also known as predictors, and the acquisition of a suitable dataset. This process involves identifying key factors that may influence the outcome of software projects, such as project size, complexity, development methodologies, and team composition. Subsequently, the dataset is divided into two distinct sets: the training set and the testing set. The training data serves as the foundation for model development, where algorithms are trained and fine-tuned to learn patterns and relationships within the data. Meanwhile, the testing data is reserved for evaluating the performance of the trained models, providing an independent measure of their predictive accuracy and generalization capabilities. Upon successful development and validation, the deployed model becomes a valuable asset in the software project development lifecycle. By leveraging historical project data and learned patterns, the model can effectively forecast the future outcomes of ongoing or upcoming projects. This predictive capability empowers project stakeholders with valuable insights, enabling informed decision-making and proactive risk management throughout the software development process.

For building the model, the list of failure factors identified by Ibraigheeth and Fadzli [10] is selected to be the model input. This list of identified factors is presented in Table I. The dataset constructed in their research is also selected to fit and verify the developed models. This dataset was gathered from 236 (n = 236) failed and successful software projects and used in our research to fit and verify the developed models.

TABLE I. List of Failure Factors

ID	Failure Factor
X1	Unrealistic project objectives
X2	Team technical problems
X3	Lack of users involvement
X4	Requirements instability
X5	Problematic technology
X6	Problems in project management
X1	Unrealistic project objectives

Table II presents the sample of collected data, which identifies the six failure factors results in 10 software projects. This table illustrates the actual projects outcome (0: Success and 1: Failed).

TABLE II. Data Sample of Actual Outcome for 10 Software Projects

Project ID	Failure factors						Actual outcome
	X1	X2	X3	X4	X5	X6	
P121	0	1	0	0	1	1	0
P130	0	0	0	1	1	1	1
P131	0	1	1	0	1	1	1
P132	0	0	1	0	0	1	0
P133	0	0	1	1	1	1	1
P134	0	1	1	1	0	1	1
P143	0	0	0	1	0	0	0
P153	0	0	1	1	0	0	0
P161	0	0	0	0	1	1	0
P175	0	1	0	1	0	1	1

IV. Developing the Model

In this section, the ensemble-weighted algorithm, which combines six base prediction models, is developed.

The algorithm begins with randomly splitting the training dataset into n subsets, and then each base model is trained over all subsets. The average prediction performance for all base models over each subset is measured. Then, we identify the subset on which the base models achieved the worst average performance. The lowest performance rate indicates that this subset was the most difficult to predict. A unique “ranking number” is assigned to each base model according to its performance result over this subset.

The approach constructs four types of vectors:

1) A performance vector for each base model over all data subsets,

2) A vector represents the average performance results over each data subset for all base models,

3) A ranking vector represents the ranks of base models, and

4) A normalized weight vector represents the base models weights.

The proposed algorithm is described as follows:

a) Select the optimal predictor subset.

b) Randomly split the training dataset into n subsets.

c) Fit base models using all training data subsets.

d) Set the vector for each base model that represents the average performance for this model over each data subset. For i = 1 to k, calculate Pi,

$$\mathrm{P_i} = \frac{\mathbf{AC_i+F_i+K_i+AUC_i}}{\mathbf{4}} \quad (1)$$

where, AC is the accuracy, F is the F-measure, k is the kappa coefficient, and AUC is the area under the receiver operating characteristic curve.

e) A vector that represents the average of performance results (of all base models) is set over each data subset.

$$\mathrm{AvP_j} = \frac{\sum_{i=1}^{n} \mathrm{P_j}}{\mathrm{n}} \quad (2)$$

where, $\mathrm{AvP_j}$ is the average performance value for all base models over subset j. The subset with lowest AvP is the most difficult subset to predict.

f) A ranking vector that represents the ranks of base models according to their performance over the most difficult-to-predict data subset is set. Each base model gets a ranking number from 1 to k (k is the number of base models). The higher performance model (over the most difficult data subset) gets a higher ranking number.

g) Set a vector that represents the base model weights.

The weight of model m can be estimated by:

$$w_m = \frac{R_m P_m}{\sum_{i=1}^{k} R_i P_i} \quad (3)$$

where, k is the number of base models, and R is the base model rank (from 1 to k) over the most difficult dataset.

In the proposed algorithm, the weight assigned to each base model mm is determined by Eq. (3). This equation calculates the weight wmwm based on the rank and performance of the model mm relative to other base models in the ensemble. Here's a detailed explanation:

i) Base Model Rank R_m: The rank of a base model mm represents its performance relative to other models in the ensemble on the most challenging dataset instances. Models that exhibit better predictive capabilities or accuracy are assigned lower ranks, indicating higher effectiveness in handling difficult data instances.

ii) Base Model Performance P_m: The performance of each base model *m* is measured by its predictive ability or accuracy. Higher performance models, which accurately predict the outcomes of software project instances, are assigned higher values for P_m.

iii) Normalization Factor $\sum_{i=1}^{k} R_i P_i$: This term represents the sum of the ranks multiplied by the corresponding performance measures for all base models in the ensemble. It acts as a normalization factor to ensure that the weights w_m sum up to 1, thereby maintaining the integrity of the weighted ensemble.

h) The final predicted value Pr (probability of failure) is obtained according to each base model weight:

$$\mathrm{Pr} = \sum_{i=1}^{k} w_i D_i, \quad (4)$$

where, Di is the predicted value of base model i.

Eq. (4) calculates the final predicted value of the probability of failure (Pr) based on the weighted contributions of each base model in the ensemble. Here's a detailed explanation:

i) Base model weight w_i: Each base model ii in the ensemble is assigned a weight wiwi determined by its effectiveness in predicting software project failures. The weight reflects the relative importance or influence of the corresponding model in the ensemble. Models with higher weights contribute more significantly to the final prediction.

ii) Predicted value D_i: D_i represents the predicted value of failure probability by the base model ii. Each base model generates its own prediction based on its internal algorithms and training data. These predicted values represent the likelihood of failure for individual software project instances.

iii) Weighted summation: The final predicted value of failure probability (Pr) is obtained by summing the weighted contributions of all base models in the ensemble. Each predicted value D_i is multiplied by its corresponding weight wiwi, and these weighted values are summed up for all k base models in the ensemble.

By aggregating the predictions from multiple base models according to their respective weights, Eq. (4) produces a composite prediction of failure probability that leverages the strengths of individual models while mitigating the impact of potential weaknesses. This weighted ensemble approach enhances the overall accuracy and reliability of the prediction, providing a more robust assessment of the likelihood of failure for software project instances.

To illustrate the algorithm, a simple example of ensemble with three base models and three data subsets is considered. We define P = (P1| P2 |P3) and let P1 = (0.77, 0.66, 0.84), P2 = (0.78, 0.90, 0.81) and P3 = (0.97, 0.60, 0.78), where Pi represents the performance vector of base model i over the three data subset. We obtain AvP = (0.84, 0.72, 0.81), which indicates the average performance of the three base models over the three data subset. According to AvP values, the second data subset was the most difficult subset to predict as it gets the lowest average performance score (0.72). Therefore, we rank the base models according to their performance results over the most difficult subset to predict. The second base model will get the higher rank number = 3 as it achieved a higher performance (0.90) result over the most difficult subset. The rank number = 2 is given to first base model, and rank number = 1 is given to the third base model. The normalized weight vector W=(0.286,0.584,0.13) is obtained by:

$$W = \left(\frac{\mathbf{0.66 \times 2}}{(\mathbf{0.66 * 2})+(\mathbf{0.90 \times 3})+(\mathbf{0.60 \times 1})}, \frac{\mathbf{0.90 \times 3}}{(\mathbf{0.66 \times 2})+(\mathbf{0.90 \times 3})+(\mathbf{0.60 \times 1})}, \frac{\mathbf{0.60 \times 1}}{(\mathbf{0.66 * 2})+(\mathbf{0.90 \times 3})+(\mathbf{0.60 \times 1})}\right)$$

$$W = (0.286, 0.584, 0.13)$$

The highest weight is given for the second base model as it obtained a higher rank according to its performance in predicting the most difficult data subset to predict.

Finally, the prediction value for each data instant is obtained based on the above base model weights. Suppose that the three base models generate probabilities of failure: 0.66, 0.35, and 0.74; therefore, the final failure probability Pr generated by the model based on the estimated weight is 0.49.

$$Pr=(0.286 \times 0.66)+(0.584 \times 0.35)+(0.13 \times 0.74)= 0.49$$

The failure probability result is used to classify the expected project outcome (failed/success). The default probability value 0.5 is selected to be the classification threshold, with failure expected for any result higher than 0.5. Future research can be conducted to determine the optimal threshold for determining project failure.

V. Experimental Results

For comparison purpose, in addition to building the proposed model, the experiments included running the model using four methods. Initially, the model is implemented using three of the existing individual prediction techniques: LR, SVM, and ANFIS. These methods were chosen because they showed a high efficiency in failure prediction compared with other methods in a study conducted by Ibraigheeth and Eid [6]. These three models were combined to create a simple majority voting model. To run the simple majority voting model, the training dataset is used to build the three base models (LR, SVM, and ANFIS), and then the final prediction decision for any test instance is generated by majority voting. The new weighted ensemble model is implemented and tested in terms of its ability to predict software project failures. The experiments included calculating eight performance measures: sensitivity or recall, specificity, precision, negative predictive value, accuracy, F-measure, kappa coefficient, and AUC value.

Several statistical tests were applied on the proposed model to evaluate its performance. Confusion matrix that includes information about actual and predicted model outputs is shown in Fig. 2. For the project failure prediction problem, the confusion matrix is used to evaluate the model performance. The column of the confusion matrix represents the actual result (class), while the row represents the predicted result. TP (True Positive) and TN (True Negative) denote how many instances are classified correctly, while FP (False Positive) and FN (False Negative) denote how many instants are classified incorrectly.

		Predicted output	
		+	−
Actual Output	+	T P = 12	F N = 1
	−	F P = 1	T N = 10

Fig. 2. Confusion matrix.

TABLE III. Performance Measures

Measure	Value
Sensitivity (Recall)	0.923
Specificity	0.909
Precision	0.923
Negative predictive value	0.909
Accuracy	0.916
F-measure	0.923
Kappa	0.914
AUC	0.96
Average	0.92

Several performance evaluation metrics can be generated from the confusion matrix. Table III shows performance measures of the proposed model over testing dataset.

A comparative evaluation for the proposed weighted ensemble prediction model is performed. In this paper, the ensemble model was run to predict the software project failure. Table IV shows a summary of the performance measure for the proposed ensemble model versus the simple majority voting model as well as the other three individual models: LR, SVM, and ANFIS.

Table IV shows that the proposed weighted ensemble model has the highest values for most of performance measures; it has an average performance of 92% compared with 89% for the proposed majority voting model, 81% for LR model, 82% for SVM model, and 83% for ANFIS. Experiments also prove that the simple majority-voting model performs better than individual models.

TABLE IV. Proposed Weighted Ensemble Predictive Model Performance Measures

Measure	Proposed weighted ensemble model	Simple majority voting model	LR	SVM	ANFIS
Sensitivity (Recall)	0.92	0.92	0.85	0.77	0.81
Specificity	0.90	0.84	0.77	0.91	0.96
Negative predictive value	0.92	0.87	0.89	0.90	0.96
Accuracy	0.90	0.90	0.71	0.83	0.82
Precision	0.91	0.89	0.83	0.84	0.88
F-measure	0.92	0.90	0.87	0.83	0.88
Kappa	0.91	0.86	0.79	0.69	0.77
AUC	0.96	0.94	0.94	0.84	0.62
Average	0.92	0.89	0.81	0.82	0.83

Table V illustrates a sample of the data of 10 software projects and their corresponding actual outcome, the proposed weighted ensemble model predicted outcome. The table illustrates that all projects except P16 were labeled correctly. Projects P11, P13, P17, P19, and P20 were correctly labeled as failed projects with actual outcome = 1, and Projects P12, P14, P15, and P18 were correctly labeled as success projects with actual outcome =0. Project P16 was inaccurately labeled as success (Predicted outcome = 0) when the projects were failed (Actual outcome = 1).

In the comparative evaluation of the proposed weighted ensemble prediction model, the analysis delves into its performance in relation to alternative methodologies. By subjecting the ensemble model to prediction tasks for software project failure, a comprehensive understanding of its efficacy is garnered. Table IV elucidates the performance metrics, showcasing the superiority of the proposed weighted ensemble model over the simple majority voting model and individual models such as LR, SVM, and ANFIS. Notably, the ensemble model consistently achieves higher performance across various metrics, with an average accuracy of 92%, outperforming its counterparts. Moreover, insights gleaned from experimentation highlight the advantageous nature of employing a simple majority-voting model over relying solely on individual models. As the software industry navigates complex project landscapes, such evaluations play a pivotal role in informing decision-making processes and shaping future research directions

TABLE V. SAMPLE OF ACTUAL AND PREDICTED OUTCOMES

Project ID	Actual outcome	Predicted outcome
P 1 1	1	1
P 1 2	0	0
P 1 3	1	1
P 1 4	0	0
P 1 5	0	0
P 1 6	0	1
P 1 7	1	1
P 1 8	0	0
P 1 9	1	1
P 20	1	1

VI. CONCLUSION

In this paper, a new ensemble weighted model is proposed for predicting software project failures. The proposed algorithm incorporates six base models to provide the final decision of the software project outcome. These models are: NNs, LR, SVM, NB, ANFIS, and DT. We suggest that the different prediction abilities of these six methods enable the proposed algorithm to capture different characteristics of the training data and produce more reliable and accurate prediction. The proposed algorithm assigns a unique “ranking number” to each base model according to its ability to predict the most difficult data. Higher performance base models over the most difficult-to-predict data will be assigned higher ranking numbers. A normalized weighted vector is constructed based on these ranking numbers, and the final predicted value is obtained based on the weight assigned for each base model.

In the empirical analysis, eight performance measures are used to evaluate the proposed model performance. The research proves that the weighted ensemble model outperforms the simple majority voting and the individual prediction models. The experiments have also shown that the simple majority-voting model outperforms the other three individual models.

As this paper introduces a novel ensemble weighted model for predicting software project failures, future work could explore several avenues to enhance and extend the proposed approach. Firstly, further investigation could be conducted into the selection and incorporation of additional base models beyond the six currently utilized (NNs, LR, SVM, NB, ANFIS, and DT). This exploration may involve considering emerging machine learning techniques or domain-specific models tailored to software project prediction tasks. Additionally, research efforts could focus on refining the methodology for assigning ranking numbers to base models based on their predictive capabilities across different data instances. Fine-tuning this ranking system could potentially lead to more accurate and nuanced weighting of base models, thereby improving the overall performance of the ensemble model. Furthermore, the evaluation framework utilized in this study could be expanded to include additional performance metrics or consider alternative evaluation methodologies to provide a more comprehensive assessment of the proposed model's efficacy. Lastly, real-world deployment and validation of the model within software development environments could offer valuable insights into its practical utility and effectiveness in mitigating project failure risks. By addressing these future research directions, advancements can be made towards developing more robust and reliable predictive models for software project management.

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Detection of Personal Protective Equipment (PPE) using an Anchor Free-Convolutional Neural Network

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***Abstract*—In industrial environments, the utilization of Personal Protective Equipment (PPE) is paramount for safeguarding workers from potential hazards. While various PPE detection methods have been explored in the literature, deep learning approaches have consistently demonstrated superior accuracy in comparison to other methodologies. However, addressing the pressing research challenge in deep learning-based PPE detection, which pertains to achieving high accuracy rates, non-destructive monitoring, and real-time capabilities, remains a critical need. To address this challenge, this study proposes a deep learning model based on the Yolov8 architecture. This model is specifically designed to meet the rigorous demands of PPE detection, ensuring accurate results. The methodology involves the creation of a custom dataset and encompasses rigorous training, validation, and testing processes. Experimental results and performance evaluations validate the proposed method, illustrating its ability to achieve highly accurate results consistently. This research contributes to the field by offering an effective and robust solution for PPE detection in industrial environments, emphasizing the paramount importance of accuracy, non-destructiveness, and real-time capabilities in ensuring workplace safety.**

Keywords—PPE detection; deep learning; YOLOv8; industrial environments; real-time detection

I. INTRODUCTION

Personal Protective Equipment (PPE) plays a pivotal role in ensuring the safety of workers in industrial environments [1], [2]. The first line of defense against potential hazards, PPE includes various gear such as aprons, gloves, helmets, masks, and shoes designed to protect workers from physical, chemical, and biological risks [3]. Proper detection and monitoring of PPE utilization in industrial settings are of paramount importance to guarantee workplace safety [4]. This paper delves into the realm of PPE detection, highlighting its significance and examining the latest advancements in technology for this purpose [5].

The accurate detection of PPE, including aprons, gloves, helmets, masks, and shoes, in industrial environments is crucial for safeguarding workers from potential hazards. PPE detection ensures that employees are equipped with the necessary gear, minimizing the risk of injuries and health issues. The ability to monitor PPE utilization is instrumental in maintaining a safe work environment, not only for individuals but also for the overall efficiency of industrial operations [6]. To address the need for effective PPE detection, a range of technologies has been developed over the years. In this paper, we review existing methods and explore the latest advances in PPE detection techniques. These advancements in technology are essential for real-time monitoring of PPE usage and ensuring the utmost safety in industrial workplaces [8].

Deep learning-based approaches have gained significant attention in recent years for PPE detection [7]. These methods have become a focal point of research due to their exceptional ability to handle complex visual data and patterns. In comparison to traditional methods, deep learning offers superior accuracy and robustness in detecting PPE items. This paper provides insights into why deep learning-based approaches have garnered immense interest among researchers and have become a promising avenue for addressing PPE detection challenges [9].

Despite the potential of deep learning-based approaches, there exist certain limitations and research challenges. These include the demand for high accuracy and real-time requirements. In this paper, we emphasize the need for further exploration and research to overcome these challenges, underscoring the importance of striving for methods that can fulfill the rigorous demands of PPE detection in industrial settings.

In response to these challenges, this study proposes a deep learning method based on Convolutional Neural Networks (CNN) to address the complexities of PPE detection [10]–[12]. We provide a justification for adopting this deep learning approach and demonstrate how it can effectively resolve the research challenges and provide high-accuracy real-time PPE detection. The study involves the creation of a custom dataset and encompasses training, validation, and testing processes to ensure the robustness of the proposed method.

This research contributes to the field of PPE detection in several ways. First, it generates a custom dataset specifically designed for PPE detection challenges, enriching the available resources for future research in this domain. Second, it introduces an efficient deep-learning method tailored to the unique requirements of PPE detection. Lastly, extensive experiments and performance evaluations are conducted to validate the effectiveness of the proposed method, offering a comprehensive assessment of its capabilities and practical applications.

II. PREVIOUS STUDY

The realm of agriculture has seen remarkable progress, primarily propelled by the substantial contributions of machine learning and deep learning techniques. These state-of-the-art technologies have been instrumental in reshaping the prediction, classification, and identification of Personal Protective Equipment (PPE). Their integration offers a multitude of benefits, including non-invasiveness, cost-effectiveness, speed, and reliable PPE detection. This transformative potential has sparked numerous research endeavors dedicated to enhancing PPE diagnosis and detection.

This paper in [13] presented a Convolutional Neural Network (CNN) method for identifying Personal Protective Equipment (PPE) usage compliance in manufacturing laboratory settings. The CNN model is trained on a custom dataset and demonstrates remarkable accuracy in recognizing various PPE items, including aprons, gloves, helmets, masks, and shoes. However, a limitation of the approach is its sensitivity to variations in lighting conditions, which can affect detection accuracy. Future work could involve the integration of advanced lighting normalization techniques to address this limitation and further enhance the model's robustness for real-time PPE compliance monitoring in dynamic industrial environments.

The authors in study [1] introduced a deep learning-based framework for monitoring the wearing of Personal Protective Equipment (PPE) on construction sites. The method employs convolutional neural networks (CNNs) to detect and identify PPE items, ensuring compliance. However, a limitation is the challenge of real-time monitoring due to computational demands, which may impact its practical applicability. Future research could focus on optimizing the model for real-time performance to enhance its effectiveness in the dynamic and time-sensitive construction site environment.

This paper in [2] presented a Substation Safety Awareness intelligence model employing a Graph Neural Network (GNN) approach for rapid detection of Personal Protective Equipment (PPE). The GNN model effectively identifies PPE items, ensuring safety in substation environments. However, one limitation is the need for high-quality data, which may not always be readily available for model training, potentially limiting its practical implementation. Future research should explore techniques for mitigating data scarcity and enhancing model generalization to diverse substation settings.

The authors in [14] introduced a video-based smart safety monitoring system to prevent industrial work accidents. The method utilizes computer vision and machine learning algorithms to analyze video footage, detecting potential safety hazards. A limitation is that it may require substantial computational resources for real-time monitoring across extensive industrial settings. Future work should focus on optimizing computational efficiency to enhance its practicality and scalability.

This paper in [15] presented an enhanced detection network model based on YOLOv5 for safety warnings in construction sites. The method employs YOLOv5, a state-of-the-art object detection architecture, to identify potential safety hazards. However, a limitation lies in the sensitivity of the model to variations in lighting and environmental conditions, which can affect detection accuracy. Future research could focus on refining the model's robustness to lighting and environmental changes, improving its performance as a safety warning tool in dynamic construction site environments.

The five papers discussed focus on improving safety by monitoring the compliance of the PPE in various industrial contexts. They primarily employ deep learning and computer vision technologies for this purpose. While they all share the goal of enhancing workplace safety, each paper addresses a different industrial setting and applies distinct methodologies. The [13] emphasizes PPE compliance in manufacturing labs, using CNNs for detection. Its limitation is sensitivity to lighting variations. The study in [1] targets construction sites but doesn't explicitly mention limitations, hinting at potential real-time computational challenges. The study in [2] uses GNNs for rapid PPE detection in substation environments, highlighting data availability as a limitation. The study in [14] focuses on video-based safety across various industrial settings, with computational resource requirements as the main limitation. The research in [15] refines a YOLOv5-based model for construction site safety, noting sensitivity to lighting and environmental conditions. In summary, these papers contribute to safety monitoring by adapting their approaches to different industrial contexts, each with its own set of challenges and limitations. Despite common concerns, such as sensitivity to lighting and real-time computational demands, each paper offers unique insights to enhance workplace safety.

III. Methodology

A. Data Collection

We constructed our dataset by gathering PPE images from both publicly available internet resources and the Roboflow platform, aiming to create a comprehensive and diverse collection of images for training and testing. The original dataset is a collection of 3897 images of workers wearing safety vests in various industrial settings [1]. The images are annotated with bounding boxes that indicate the location and category of the safety vests. The dataset is intended for training computer vision models that can detect whether workers are wearing the PPE or not. The dataset is part of the Roboflow Universe Projects, which are open-source datasets for various computer vision tasks.

B. Data Augmentation

To ensure the dataset's richness and diversity, we employed data augmentation techniques. Data augmentation is a critical step in deep learning, especially in the context of the PPE detection, as it allows us to generate a more extensive and varied set of images, enhancing the model's ability to handle real-world scenarios. To augment our PPE dataset, we utilized common techniques such as rotation, translation, and scaling. These techniques simulate variations in object positions and orientations, which are essential for addressing real-world challenges like workers wearing PPE at different angles or in varying positions. We also applied techniques like horizontal and vertical flipping, which helps the model generalize better to PPE instances appearing both on the left and right sides of the frame.

Additionally, we used color adjustments, including brightness and contrast modifications, to account for varying

[1] https://universe.roboflow.com/roboflow-universe-projects/safety-vests

lighting conditions in industrial settings. Finally, noise injection and blurring were employed to replicate scenarios where the PPE items might be partially obscured or subject to environmental interference. These data augmentation techniques collectively enhance the dataset's diversity, making it more robust and suitable for training models capable of handling a wide range of real-world PPE detection scenarios. After the data augmentation process the size of dataset is tripled and the new size of the dataset in this study is 11691.

C. PPE Model Object Detection

There are several compelling reasons to consider utilizing YOLOv8 in our computer vision project:

1) Enhanced accuracy: YOLOv8 boasts improved accuracy compared to its predecessors, making it an attractive choice for various computer vision tasks.

2) Feature-rich implementation: The latest YOLOv8 implementation introduces a wealth of new features, with a particularly user-friendly Command Line Interface (CLI) and a dedicated GitHub repository. These additions streamline development and project management.

3) Versatility: YOLOv8 supports multiple computer vision tasks, including object detection, instance segmentation, and image classification, providing a comprehensive solution for various applications.

4) Efficient training: YOLOv8 offers faster training times in comparison to some other two-stage object detection models, making it a more time-efficient option for our computer vision projects.

The layout created by [16] offers an excellent visualization of the architecture, providing a clear and structured representation of the system. This visual aid can significantly enhance understanding and communication of complex concepts or technical architectures within the context of software development or any other field. In this study, a Yolov8 based method is proposed for PPE object detection. Fig. 1 shows the proposed system architecture.

Anchor-free detection refers to a method where an object detection model directly predicts the center of an object, eliminating the need to calculate the offset from a predefined anchor box.

In contrast, anchor boxes are predetermined bounding boxes with specific height and width characteristics. These boxes are strategically chosen based on the size and aspect ratio of objects present in the training dataset. During the detection process, these anchor boxes are systematically arranged and tiled across the image.

The network's output includes probabilities and attributes for each of these tiled boxes, encompassing information like background, Intersection over Union (IoU), and offset values. These attributes are instrumental in adjusting the anchor boxes. Multiple anchor boxes can be created to accommodate objects of various sizes, functioning as fixed reference points for predicting bounding boxes. An illustration depicting bounding box predictions based on anchor boxes is depicted in Fig. 2.

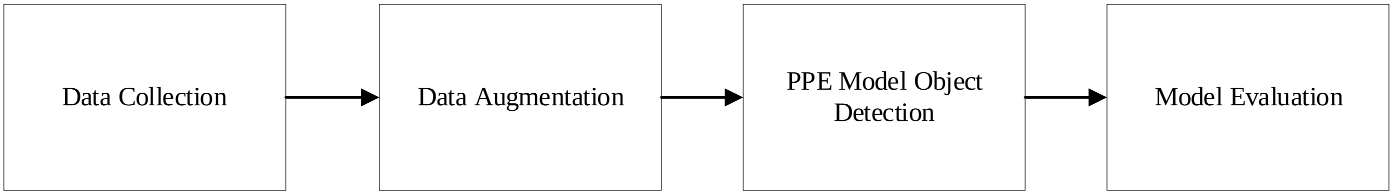

Fig. 1. The proposed system architecture.

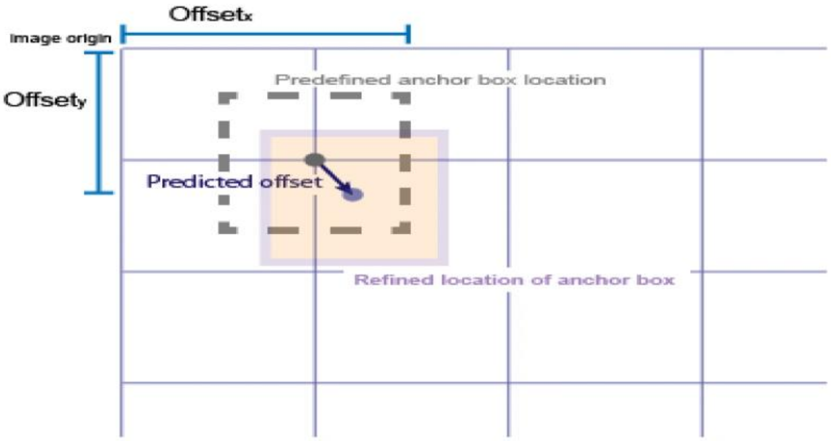
Offsetx
Image origin
Offsety
Predefined anchor box location
Predicted offset
Refined location of anchor box

Fig. 2. An illustration depicting bounding box predictions based on anchor boxes.

Anchor-free detection offers notable advantages due to its flexibility and efficiency. Unlike methods that rely on predefined anchor boxes, anchor-free detection eliminates the need for manually specifying these anchors. In previous YOLO models like v1 and v2, selecting anchor boxes was a challenge and could result in suboptimal outcomes. Anchor-free detection simplifies this aspect, allowing for more adaptability in object detection tasks.

D. Model Evaluation

To evaluate the performance of a YOLOv8 model for PPE detection using precision, recall, and mean Average Precision (mAP) metrics, we'll assess the model's ability to detect and localize PPE items in images correctly. Here's how we calculate these metrics and their formulas:

Precision measures the accuracy of positive predictions made by the model.

Precision = True Positives (TP) / (True Positives + False Positives)

True Positives (TP) are the number of correct PPE detections.

False Positives (FP) are the number of instances where the model incorrectly predicts PPE when there is none.

Recall, also known as sensitivity or true positive rate, measures the model's ability to identify all relevant PPE instances.

Recall = True Positives (TP) / (True Positives + False Negatives)

True Negatives (TN) are the number of instances where the model correctly predicts the absence of PPE.

False Negatives (FN) are the number of actual PPE instances that the model misses.

(mAP) is a comprehensive metric used in object detection tasks to assess the model's performance. It calculates the average precision at various confidence thresholds and is often visualized as a precision-recall curve. The mAP formula involves the following steps:

- Calculate precision and recall for different confidence thresholds.
- Calculate the area under the precision-recall curve.
- Average the areas under the curve for different classes, resulting in the mAP.

mAP provides a holistic view of the model's performance across various levels of confidence in detecting PPE items. A higher mAP indicates a more reliable and accurate model.

These metrics collectively provides a quantitative assessment of the YOLOv8 model's ability to detect PPE items in terms of accuracy, completeness, and overall performance. Evaluating precision, recall, and mAP helps we understand the model's strengths and weaknesses, enabling us to fine-tune it for improved PPE detection accuracy.

In this study, a YOLOv8 model was generated for the purpose of PPE detection on a custom dataset. The dataset was initially divided into three sets: 70% for training, 20% for validation, and 10% for testing. This division ensures a robust evaluation of the model's performance while preventing overfitting and enabling efficient training. For training the YOLOv8 model, the dataset was utilized to teach the model to recognize PPE items. The training process involved passing the dataset through the model multiple times iteratively adjusting the model's parameters to improve accuracy. In the context of improving PPE detection accuracy, it is advisable to consider a few key details. Firstly, an optimal learning rate should be selected, typically through experimentation, to ensure the model converges effectively. It's recommended to start with a lower learning rate and gradually increase it as necessary. Batch size is another crucial factor; larger batches can accelerate training but may require more memory. Striking the right balance is essential. Augmentation techniques such as rotation, translation, and color adjustment can further improve accuracy by diversifying the training data.

Furthermore, the dataset should be balanced, meaning that it should contain an equal distribution of PPE and non-PPE examples. This avoids bias and helps the model achieve better accuracy in detection. The validation module is pivotal in monitoring the model's performance. It assesses the model's generalization capability and helps identify any potential overfitting. In the context of PPE detection accuracy improvement, the validation set should be representative of real-world scenarios. Hyperparameter tuning is typically performed here, experimenting with various learning rates, batch sizes, and data augmentation techniques. The aim is to find the configuration that optimizes PPE detection accuracy without compromising the model's ability to generalize to unseen data. The testing module evaluates the YOLOv8 model's performance on an independent dataset, ensuring that it can accurately detect PPE items in real-world situations. To enhance PPE detection accuracy, the testing set should be diverse and representative of the environments in which the model will be deployed. This module is instrumental in quantifying the model's accuracy and assessing its readiness for real-world applications. The model's performance can be measured using metrics like precision, recall, and F1-score, which should be optimized to achieve the desired PPE detection accuracy.

In conclusion, to generate a YOLOv8 model for PPE detection, it is crucial to carefully consider training details such as learning rate, batch size, and data augmentation techniques. Balancing the dataset and ensuring diversity in the validation and testing sets are essential for accurate model evaluation. These suggestions should be tailored to the specific requirements of improving the accuracy of PPE detection, ensuring the model performs effectively in real-world scenarios

The Precision-Confidence Curve is a critical evaluation tool for assessing the performance and efficiency of a PPE detection model, such as YOLOv8s. It provides valuable insights into how the model's confidence in its predictions relates to the precision it achieves for various object classes. This curve helps in understanding the model's effectiveness and its ability to make accurate predictions while maintaining high precision. In this case, where we are detecting PPE items, including classes like aprons, gloves, helmets, masks, and shoes, achieving a high precision rate of approximately 0.95 for all classes is an exceptional accomplishment. It means that when the model makes a prediction for any of these classes, there is a very high likelihood that the prediction is correct, with very few false positives. This is particularly important in PPE detection, where ensuring the safety and compliance of individuals in industrial or medical settings is of utmost importance. The precision confidence curve of the model is depicted in Fig. 3.

The high precision values, nearly 0.95, across all classes in the Precision-Confidence Curve indicate the model's effectiveness in recognizing PPE items. It demonstrates the model's ability to confidently identify and localize these items, contributing significantly to safety and compliance. With such high precision, the model can be relied upon to provide accurate PPE detection, which is crucial for preventing accidents, maintaining safety standards, and ensuring that individuals are adequately protected. These values instill confidence in the model's performance and highlight its efficiency in recognizing PPE classes, underlining its practical utility in real-world applications.

The Recall-Confidence Curve is a crucial tool for evaluating the efficiency of a YOLOv8s model in PPE detection. Fig. 4 illustrates how the model's confidence in its predictions correlates with the recall it achieves for various PPE classes. The model's exceptional performance is evident, with an approximate 0.84 recall rate at the maximum confidence level across all classes. This means that the model effectively captures the majority of actual PPE instances, reducing the risk of missing important items and enhancing safety compliance in industrial and medical settings. The YOLOv8s model, as demonstrated by the Recall-Confidence Curve, proves to be highly efficient in recognizing PPE classes. These high recall values emphasize its effectiveness in minimizing the risk of overlooking critical PPE items and contribute significantly to maintaining safety standards and preventing accidents in real-world applications.

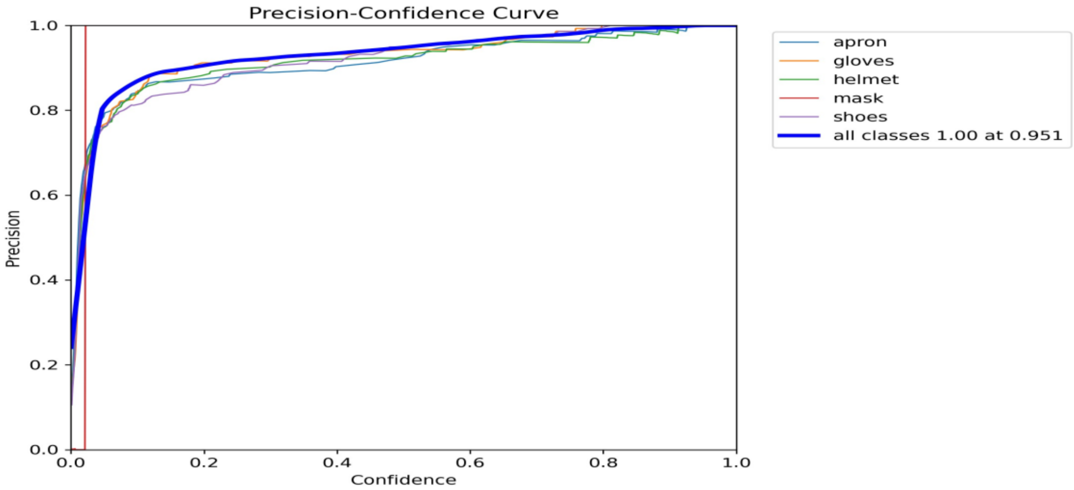

Fig. 3. Precision confidence curve of the model.

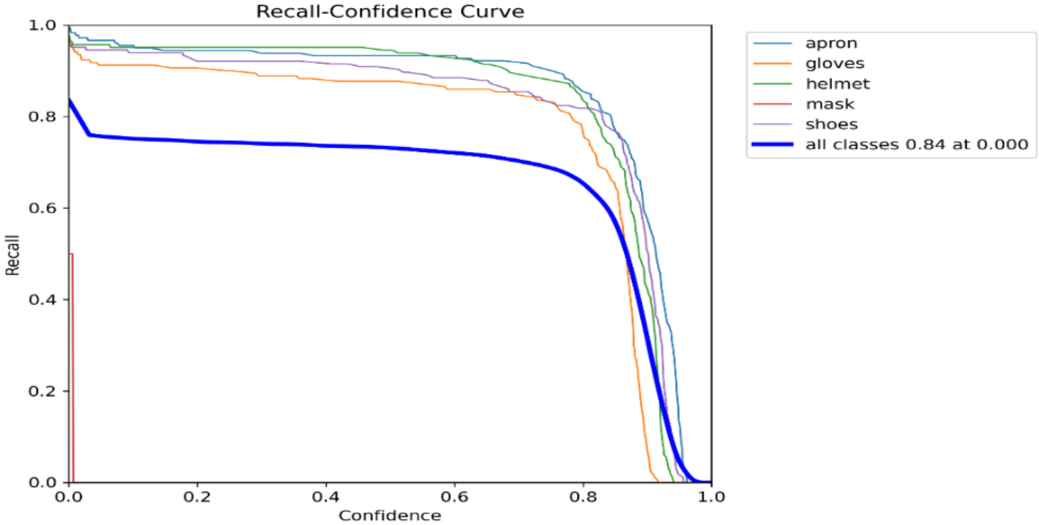

Fig. 4. Recall the confidence curve of the model.

The Precision-Recall curve is a crucial tool for evaluating the efficiency of a YOLOv8s model in PPE detection. Fig. 5 illustrates the trade-off between precision and recall, offering insights into the model's performance. The model's performance is notable, with an approximate 0.75 recall rate at the maximum confidence level across all PPE classes. This high recall rate indicates the model's effectiveness in recognizing these crucial PPE items, reducing the risk of overlooking important safety gear and enhancing safety compliance in industrial and medical settings. The YOLOv8s model, as shown by the Precision-Recall curve, is efficient and reliable in PPE detection, making it a valuable asset for maintaining safety standards and preventing accidents in real-world applications. These high recall values emphasize the model's effectiveness in minimizing the risk of missing important PPE items and contribute significantly to overall safety measures

The F1 Confidence Curve is a vital tool for evaluating the efficiency of a YOLOv8s model in PPE detection. Fig. 6 provides insights into the model's confidence in its predictions and the resulting F1-score, which balances precision and recall. The model's performance is impressive, with an approximate 0.74 F1 score at the maximum confidence level across all PPE classes. This high F1-score indicates the model's effectiveness in accurately recognizing these essential PPE items, striking a balance between precision and recall. This balance is crucial for minimizing false alarms and missed detections, contributing significantly to safety compliance in various industrial and medical settings.

In conclusion, the YOLOv8s model, as demonstrated by the F1 Confidence Curve, is a robust and reliable solution for PPE detection. It excels in minimizing false alarms and ensuring that important PPE items are accurately identified, enhancing overall safety measures in real-world applications. The results of the model are depicted in Fig. 7.

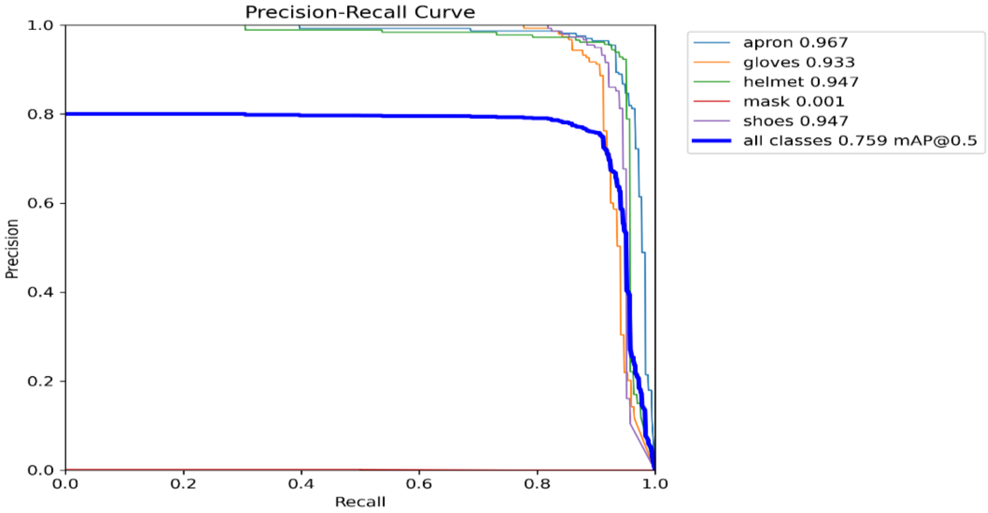

Fig. 5. Precision-Recall curve of the model.

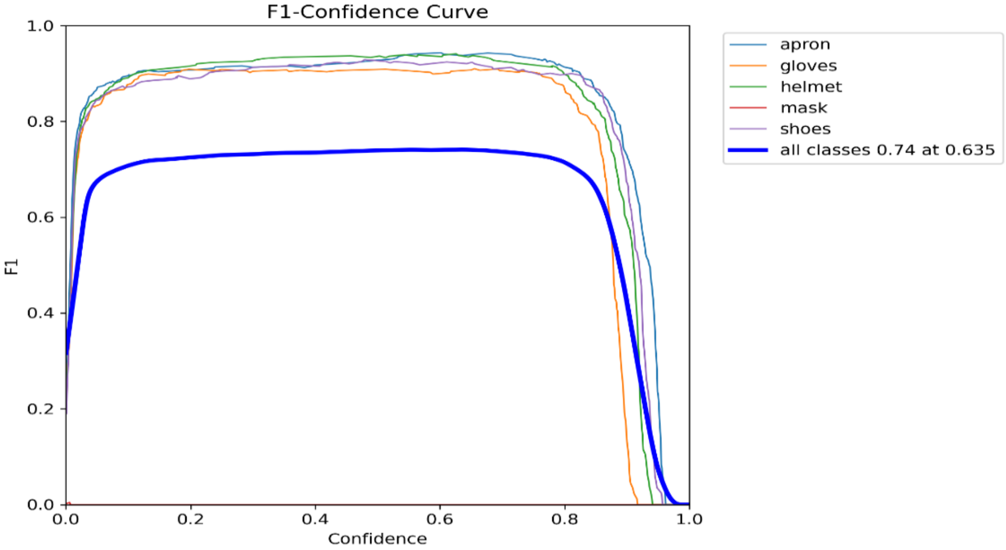

Fig. 6. F1-confidence curve of the model.

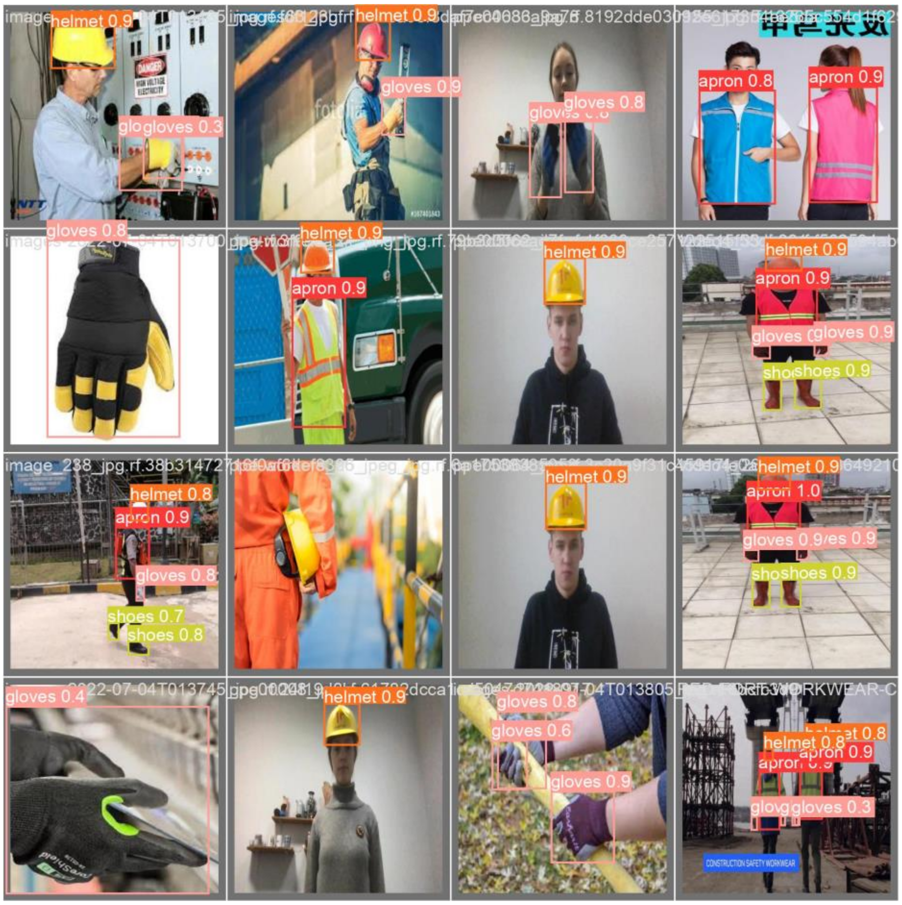

Fig. 7. The result of the model.

IV. Results And Discussion

We have performance metrics for two object detection models, YOLOv5s and YOLOv8s, both applied to Personal Protective Equipment (PPE) detection. The metrics include Precision, Recall, mAP (mean Average Precision at a confidence threshold of 0.5), and F1-score. The table shows the comparison of the results of YOLOv8s and YOLOv5s. YOLOv8s has a higher precision (0.95) compared to YOLOv5s (0.88). This means YOLOv8s makes fewer false-positive predictions, resulting in more accurate detection of PPE items. High precision is essential to minimize false alarms, ensuring accurate PPE identification.YOLOv8s has a higher recall (0.84) compared to YOLOv5s (0.78). This suggests that YOLOv8s successfully identifies a higher proportion of actual PPE items within the dataset, indicating improved completeness in detection. A higher recall means fewer missed PPE items, enhancing safety. Both YOLOv8s and YOLOv5s have good mAP values at a confidence threshold of 0.5, with YOLOv5s slightly outperforming YOLOv8s (0.76 vs. 0.75). This indicates that both models perform well in terms of precision and recall, with YOLOv5s being slightly more consistent in precision and recall trade-offs. The F1-score for both models is the same (0.74). This score represents the balance between precision and recall. YOLOv5s achieves a better balance between these two metrics, whereas YOLOv8s has a higher precision but a slightly lower recall.

In summary, YOLOv8s exhibits higher precision and slightly lower recall compared to YOLOv5s. The choice between these models depends on specific requirements. YOLOv8s is more accurate in identifying PPE and reducing false positives, but it may miss some items. YOLOv5s provides a good balance between precision and recall, which might be preferable in scenarios where minimizing false alarms is crucial. Ultimately, the choice depends on the trade-off between precision and recall that aligns with the specific PPE detection objectives. A graph of the comparison result for the different algorithms is depicted in Table I and Fig. 8.

TABLE I. The Comparison of the Results for the Different Algorithms

Model	Precision	Recall	mAP0.5
YOLOv5s	0.88	0.78	0.76
YOLOv8s	0.95	0.84	0.75
Faster R-CNN	0.92	0.82	0.78
SSD	0.89	0.80	0.73
RetinaNet	0.93	0.82	0.74

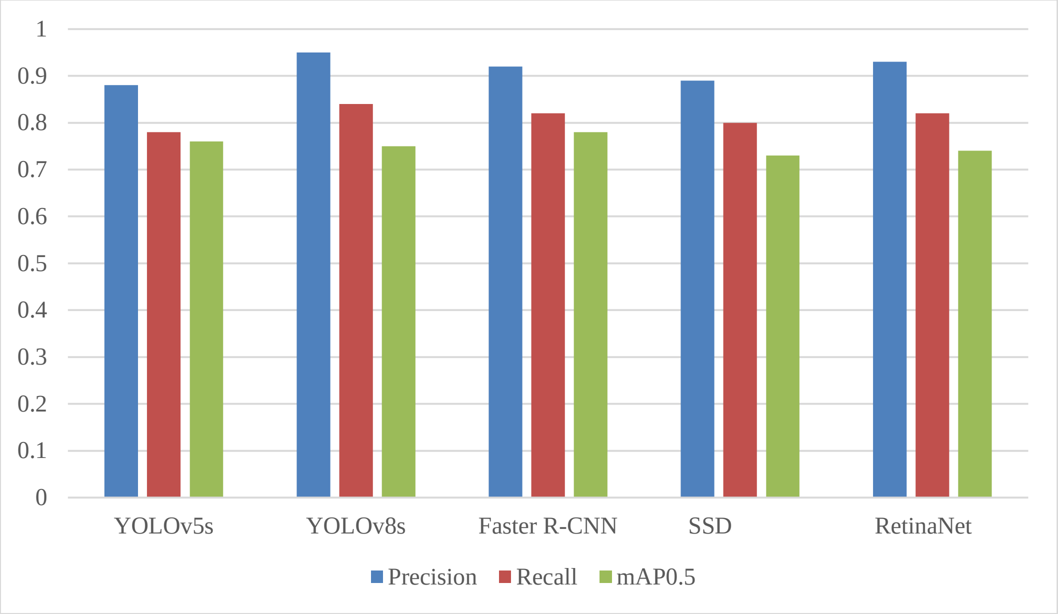

Fig. 8. Graph of the comparison result for the different algorithms.

The Table I and Fig. 9 present the performance metrics of various object detection algorithms, namely YOLOv5s, YOLOv8s, Faster R-CNN [17], RetinaNet [18], and SSD [19] in the context of PPE detection. YOLOv8s stands out with the highest precision of 0.95, indicating its ability to correctly identify PPE items with minimal false positives. This precision score suggests that YOLOv8s is adept at distinguishing between positive and negative predictions, crucial for applications where false alarms can have significant consequences. Additionally, YOLOv8s achieves a recall of 0.84, demonstrating its effectiveness in capturing a substantial portion of PPE instances present in the images. This balance between precision and recall is indicative of YOLOv8s' robust performance in detecting PPE across various scenarios.

Faster R-CNN also performs admirably with a precision of 0.92 and a recall of 0.82, closely trailing behind YOLOv8s. This indicates that Faster R-CNN is capable of achieving high accuracy in PPE detection, albeit with a slightly lower recall compared to YOLOv8s. Meanwhile, RetinaNet showcases competitive performance with a precision of 0.93 and a recall of 0.82, indicating its effectiveness in accurately identifying PPE items. However, SSD lags behind slightly with a precision of 0.89 and a recall of 0.80, suggesting that it may struggle with certain aspects of PPE detection compared to the other algorithms.

As result, YOLOv8s emerges as the algorithm with the overall best performance for PPE detection based on the provided metrics. Its combination of high precision and recall, along with a competitive mAP0.5 score, demonstrates its superiority over other models in accurately identifying PPE items. While Faster R-CNN and RetinaNet also exhibit strong performance, YOLOv8s' consistently high precision and recall make it the preferred choice for PPE detection tasks where both accuracy and reliability are paramount.

V. Conclusion and Future Work

In industrial environments, the importance of Personal Protective Equipment (PPE) cannot be overstated, as it serves as a critical safeguard against potential hazards. While various methods for PPE detection have been explored in the literature, deep learning approaches have emerged as frontrunners, consistently delivering superior accuracy. However, a pressing research challenge persists in deep learning-based PPE detection, revolving around the need for even higher accuracy, non-destructiveness, and real-time capabilities, as evidenced by previous studies. In response to this challenge, this study proposes a deep learning model utilizing the YOLOv8 architecture, specifically designed to address the demanding accuracy, non-destructive, and real-time requirements. The model is trained on a custom dataset and validated to ensure robust performance, and extensive experiments and performance evaluations are conducted to demonstrate its effectiveness. In this study, a dataset is generated with extensive diversity of images, aiming to cover a wide array of scenarios relevant to PPE detection. From varying environments to different lighting conditions and types of the PPE), the dataset ensures robustness and adaptability in algorithm training. Its scalability enables extensive training and testing, enhancing the algorithm's accuracy and generalization capabilities. By including images from diverse settings and featuring different types of PPE, the dataset enriches the learning process, equipping algorithms to detect PPE across a range of real-world situations. Ultimately, this dataset serves as a valuable resource for developing accurate and reliable PPE detection algorithms, vital for workplace safety and compliance. The experimental results and performance evaluation underscore the proposed method's ability to achieve remarkable accuracy, making it a promising solution for PPE detection in industrial environments, satisfying the stringent demands of accuracy, non-destructiveness, and real-time functionality. Two limitations in PPE detection methods are, first, the potential difficulty in differentiating between visually similar PPE items, such as gloves and protective sleeves, which could lead to misclassifications and compromise safety. Second, current PPE detection models may struggle in highly dynamic industrial environments, where the rapid movement of workers and changing scenes can hinder real-time tracking and detection accuracy. To address these limitations, two potential future research directions could be: Exploring advanced computer vision techniques, such as fine-grained object recognition and fusion with other sensor data, to improve the discrimination between visually similar PPE items, enhancing the model's precision. Investigating the integration of state-of-the-art real-time tracking algorithms and more sophisticated motion analysis to enhance PPE detection in dynamic industrial settings, ensuring accurate and reliable monitoring in high-speed, constantly changing work environments. Moreover, evaluation of different dataset is suggested to investigate the performance of the method on others scenarios.

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DeepBiG: A Hybrid Supervised CNN and Bidirectional GRU Model for Predicting the DNA Sequence

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***Abstract*—Understanding the deoxyribonucleic acid (DNA) sequence is a major component of bioinformatics research. The amount of biological data increases tremendously. Hence, there is a need for effective approaches to handle the critical problem in the general computational framework of DNA sequence prediction and classification. Numerous deep learning languages can be used to complete these tasks compared to manual techniques that have been followed for ages. The aim of this project is to employ effective approaches for pre-processing DNA sequences and using deep learning languages to train the sequences for making judgments, predictions, and classifications of DNA sequences into known categories. In this study, the pre-processing methods include k-mers and tokenization. We employ a novel hybrid deep learning algorithm that combines convolutional neural networks and is followed by bidirectional gated recurrent networks. This combination can capture dependencies within the genome sequence, even in large datasets with a lot of noise. The proposed model is compared with existing widely used models and classifiers. The results show that the proposed model achieves a good result with an accuracy of 82.90%. The dataset consists of 44,391 labeled DNA sequences obtained from the Encode project.**

Keywords*—DNA sequencing; deep learning; convolutional neural networks; bidirectional gated recurrent; k-mer; tokenizing

I. Introduction

Deoxyribonucleic acid (DNA) is unique. It contains a list of genetic codes which look likes no order random letters of adenine (A), cytosine (C), guanine (G), and thymine (T). Eventually, it is organised into little chunks that carry a set of meaning instructions for how to build and maintain body. The little chunks in known as genes. Most genes are alike to each other, only a small number of genes are slightly different between people, that resulted the uniqueness physical features. Genes instruct cells how to make proteins. As we need protein to repair cells and make a new ones for growth and maintenance of tissues. Our body proteins suppose is a constant state of turnover. Nevertheless, errors happen during the journey from genes to protein, it can develop into unhealthy genes and cause cells abnormal in growing.

To discovery these abnormal ChIP-seq is relying on experimental analysis the structures of DNA binding sequences [3], [4], [5]. These experimental analysis usually is time consuming [6], [7]. With quick expansion in the amount of genomic DNA, there is a need for efficient methods in predicting ChIP-seq allows the binding sites of transcription factors (TF). Hence, deep learning and machine learning are widely applied in predicting the DNA sequence binding specificities.

Deep learning techniques have accomplished exceptional outcomes in computer vision [8], [9], natural language processing [10], [11], bioinformatics [12], [13] and image analysis [14], [15]. Methods based on convolutional neural networks (CNN) [16] and recurrent neural networks (RNN) [17], [18] like gated recurrent unit (GRU), long short-term memory networks (LSTM) have been proposed to analyse and predict genome DNA. These techniques have been improved to generate autonomous prediction at learning process that spot specific trends and patterns to make better decisions based on the given data.

DeepBind [19] is pioneer CNN with single convolution layer, pooling operation and fully connected network. The design demonstrates a promising result to predict the sequence specification of DNA and ribonucleic acid (RNA) binding. This has inspired the following research like DeepSHR [20], DeepSEA [21] and Dilated [22]. KEGRU [23] uses a bidirectional gated recurrent (BiGRU) unit with k-mer sequences to find RNA protein binding sites. This method allows mining long dependencies of the sequences and thus achieves good performance in binding sites. DanQ [24] is a hybrid CNN + bidirectional LSTM (BiLSTM) model that applies the capabilities of CNN in extracting DNA features and BiLSTM in handling long range dependencies in order to obtain good performance.

Despite all these studies, there is a gap in finding a fair comparison which deep learning architectures perform well in detecting DNA sequences. As some methods use one-hot to code the DNA sequences, some use k-mer. One-hot is mutual orthoganal, it ignores the DNA sequence dependencies. k-mer overcomes the issue of one-hot by adjoining DNA sequences. Hence, this paper considering k-mer for data pre-processing in finding the dependency between the genome patterns and possibility independence for the underlying genome. Next, tokenize the k sequences to prepare a bag of vocabulary for deep learning process. This research, we aim to propose hybrid deep learning with CNN and BiGRU (DeepBiG) to classify Chromatin Immunoprecipitation Sequencing (ChIP-seq) data from lymphoblastoid cells (GM12878) and K562 chronic myelogenous leukemia (CML) obtained from the Encyclopedia of DNA Elements (ENCODE). CNN consists of extraction and representation capabilities. BiGRU allows capture long-range dependencies and thus obtains good performance. Next, DeepBiG is compared with different deep learning architectures with the same parameters and same dataset. Noted that, the ability in identifying the specific ChIP-seq can significantly improve our understanding on the epigenetic mechanism of the disease, thus promoting precision in drug discovery [1], [2].

The rest of this paper is organized as follows: Section II provides the experimental processes which include data pre-processing, deep learning algorithms. Section III presents the proposed model - DeepBiG. Evaluation matrices is shown in Section IV. Section V shows the experiment results and discusses the finding. Finally, Section VI concludes the paper.

II. Materials and Methods

The dataset includes 22832 labelled ChIP-seq data GM12878 lymphoblastoid cell and 21559 labelled ChIP-seq K562 chronic myelogenous leukemia (CML) cell. GM12878 is generated by Epstein–Barr virus which may cause infectious mononucleosis. K562 is one of the immortalized myelogenous leukemia cell that may cause for cancers of the blood cells. The TF of GM12878 consists ELK1 (5084 ChIP-seq) and SP1(17748 ChIP-seq). The TF of K562 consists ARID3A (9526 ChIP-seq) and CTCFL (12033 ChIP-seq). The dataset are obtained from Encode which has been processed and been provided in [19]. There are 44391 DNA cells in total and with no missing labelled. All the DNA sequences are labelled as 0 or 1. GM12878 sequences are labelled as 0 while K562 sequences are labelled as 1. Noted that the rational to choose the number of ChiP-seq is almost balance is to ensure model may perform the unbiased prediction. Saying that if given the ChIP-seq, the probability to perform the prediction manually towards the given ChIP-seq either is either GM12878 cell or K562 is about 50%.

A. Data Pre-processing

The data pre-processing steps are to transform the dataset into a uniform format that can be understood by the learning algorithms include k-mers and text tokenizer. k-mers is the common method for tokenizing the genome that splitting the long DNA sequence into k length biological sub-sequences [25], [26]. As shown in Table I, there are five k-mers where we can tokenize the sequence "AGGTCCGGGTCT". The five different k-mers will result different tokens and hence affect the performance of the language models. The k-mers range is between two until six are chosen as 1-mer will not provide any useful DNA sequence relation and accuracy prediction after 6-mers is decreased.

TABLE I. Example Biological Sub-sequences Generated by k-mers and the Number Sequence Index

v

k-mers	Biological k-mers sub-sequences	Distinct Sequence
2	AG GG GT TC CC CG GG GG GT TC CT	16
3	AGG GGT GGC TCC CCG CGG GGG GGT	64
4	AGGT GGGC GTCC TCCG CCGG CGGG GGGT	256
5	AGGTC GGTCC GTCCG TCCGG CCGGG CGGGT	1024
6	AGGTCC GGTCCG GTCCGG TCCGGT CCGGTC	4096

Tokenizer is essential to boost the performance of the natural language processing model. Firstly, creates a bag of "vocabulary" of ChiP-seq by transforming the splitting block of sequence based on k-mers into integer. For example, the bag of "vocabulary" for 2-mers ChIP-seq with 16 number of distinct sequence is 'gg'-1, 'cc'-2, 'gc'-3, 'ct'-4, 'ag'-5, 'tg'-6, 'ca'-7, 'tc'-8, 'ga'-9, 'tt'-10, 'aa'-11, 'cg'-12, 'gt'-13, 'ac'-14, 'at'-15, 'ta'-16. Next, converts the long ChIP-seq into integer based on the bag of "vocabulary", such that given the sequence "AGGTCCGGGTCT", the tokenizing output based on 2-mers is (5, 1, 13, 8, 2, 12, 1, 1, 13, 8, 4).

B. Convolutional Neural Networks (CNN)

Convolutional neural networks is deep neural networks that widely applied at the artificial intelligence research fields such that bioinformatics [27], [28], visual imagery [29] and natural language processing [30]. The design of CNN is composed of three layers, there are convolutional, pooling and fully connected layers. The layers of convolutional and pooling are designed to adaptive learn local information of original features, then extract and represent the spatial hierarchies features from low to high patterns through several feature maps and kernels. The layer of fully connected performs classification that maps the extracted features into final output. More specifically, a convolutional layer and pooling layer computes [31],

$$\begin{aligned} convolutional(X)_{i,k} &= Relu(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} W^{k}_{mn} X_{i+m,n}) \\ pooling(Y)_{ik} &= max(Y_{iP,k}, Y_{iP+1,k}, ..., Y_{iP+P-1,k}) \end{aligned} \quad (1)$$

where X is the input matrix, i is index of output position, k is the filter index, W^k is an MxN matrix. Y is the output of convolutional layer. P is the pooling.

C. Gated Recurrent Unit (GRU)

Gated recurrent unit network [32] is a deep learning machine learning that to process and to uncover the underlying relationship for a given sequences of data. The data can be text, speech, video and images. Human brain activates the process of acquiring information, forgetting and memory. The memory can be long or short. The long-term memory is applied if the matters are important. Otherwise, we tend to forget, which called short-term memory. GRU is modeled like a human brain which consists the process of reset and update. The reset process help captures short-term dependencies in sequence. The update process help captures long-term dependencies in sequence. The inputs are h_{t-1} and x_t. The reset and update processes consist of two gates to manage the cell state's information. The two gates we denoted it as z_t and r_t, where z_t is the reset gate and r_t is update gate. W_z and W_r are two weight matrices as well as $b_z and b_r$ are two bias value corresponding to these two gates. The two gates are composed by a sigmoid neural net layer (σ) and a pointwise multiplication operation. The candidate hidden state we denoted it as $\hat{C}_t$. Here, $tanh$ function is activated. The t_t is the hidden state. The value of z_t is either close one or close zero. Old state is retained, if value of z_t is closed to one. Otherwise, new latent state t_t.

Noted that, these layers are repeating and form a chain. The gate structures and cell states are calculated as follows [32]:

$$\begin{aligned} z_t &= \sigma(W_z x_t + V_z h_{h-1} + b_z) \\ r_t &= \sigma(W_r x_t + V_r h_{h-1} + b_r) \\ \hat{C}_t &= tanh(W_C x_t + V_C(r_t.h_{t-1}, x_t)) \\ t_t &= z_t.h_{t-1} + (1 - z_t).\hat{C}_t \end{aligned} \tag{2}$$

D. Bidirectional GRU (BiGRU)

Bidirectional GRU [33] accomplishes the training without the limitation of using input information just up to a present future frame. It predicts the sequence for each class using finite sequence based on the context of elements of past and future. One can see the two GRUs are executed parallel, one is forward and another one is backward. Eq. 3 and 4 shows the calculation of BiGRU that takes L inputs and H number of hidden units. The final output of BiGRU is based on the hidden BiGRU forward and backward values [33].

$$a_h^t = \sum_{l=1}^{L} x_l^t.w_{lh} + \sum_{h',t>0}^{H} b_{h'}^{t-1}.w_{h'h} \tag{3}$$

$$a_t^h = \theta_h(a_t^h) \tag{4}$$

III. The Proposed Model (DeepBiG)

CNN architecture consists of convolutional layer, pooling layer and fully connected layer. The proposed model is composed with the modified CNN architecture by replacing the fully connected layer with bidirectional GRU (BiGRU), the first two layers are remained, which is shown in Fig. 1. The rational of this design that remains the CNN first two layers to shorten the training time while maintains the accuracy during data processing by generalizing ChIP-seq patterns. Next, replacing fully connected layer with the BiGRU is to deal with the past and present order dependency information in the ChIP-seq which may efficiently characterize the highly complex order of ChIP-seq.

The first layer is a convolutional layer which is constructed with 32 filters, five kernels with rectified linear units (relu) as the activation function. During the training phase, the filters and kernels read the input matrices with same weights, produces different strengths of signals and extracts the correlation ChIP-seq patterns.

The second layer is a max pooling layer to improve the reliability and performance in term of time for the proposed model. It summarizes the feature maps so that the model will not need to be trained by maximizing the output signals of each kernel along the entire sequence.

The third layer is BiGRU to process the filtered correlated ChIP-seq with its own interpretation by considering the context of elements of past and future into its hidden state. The interpretation is further propagated to the next GRU block. Once the nucleotide is remarked, the last block of GRU makes the final decision for the goodness of the probe.

The last layer is a non-linear transformation with sigmoid activation. The sigmoid activation will produce a value between 0 and 1. This value represents the probability of a binding preference of each probe. In this case, 0 is GM12878 ChIP-seq, 1 is K562 ChIP-seq.

The proposed model is implemented based on Keras library. The experiment is undergo three phases: training, validation and testing. For the training phase, the experiment will randomly train 50% of the dataset and 25% dataset is validated at validation phase. Then, remaining 25% dataset is tested at testing phase. Early stopping is applied for overfitting. Lastly, the performance for the models are evaluated. The model is simulated on on graphical processing units (GPU) with Intel(R) Core (TM) i9-10980XE CPU@ 3.00GHz, 128GB random access memory and 1T hard disk.

IV. Performance Metrics

A confusion metric is used to assess the performance of the models on the data as shown in Table II. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are four assessment elements formulated in the confusion matrix table. TN is both predict and actual events fall on GM12878 ChIP-seq. The sequence is not K562 ChIP-seq. FP is prediction is the model incorrectly classified GM12878 ChIP-seq as K562 ChIP-seq. FN is the prediction is GM12878 ChIP-seq but the actual is K562 ChIP-seq. TP is both predict and actual events fall on K562 ChIP-seq that are correctly classified by the model.

TABLE II. Confusion Matrix

	GM12878 seq	K562 seq
GM12878 seq	True Negative (TN)	False Positive (FP)
K562 seq	False Negative (FN)	True Positive (TP)

With this matrix, one may evaluate the performance of the design model based on accuracy, precision, recall, and F1-score are as follows.

1) Accuracy: Accuracy refers to how close a measurement is to the accepted value. As shown in Eq. 5 [34], the accuracy is the proportion of correct predictions for both true positive and true negative. High accuracy requires high precision and high trueness.

$$Accuracy(A) = \frac{TP + TN}{TP + FP + FN + TN} \tag{5}$$

2) Precision: Precision refers to positive predictive value. As shown in Eq. 6 [34], the precision is the fraction of correct predictions among the true and false positive (such as correct predict the DNA sequence is K562 ChIP-seq). High precision requires high trueness.

$$Precision(P) = \frac{TP}{TP + FP} \tag{6}$$

3) Recall: Recall refers to sensitivity of the model in capturing true positive value. As shown in Eq. 7 [34], the recall value is the fraction of correct predictions among the actual positive value.

$$Recall(R) = \frac{TP}{TP + FN} \tag{7}$$

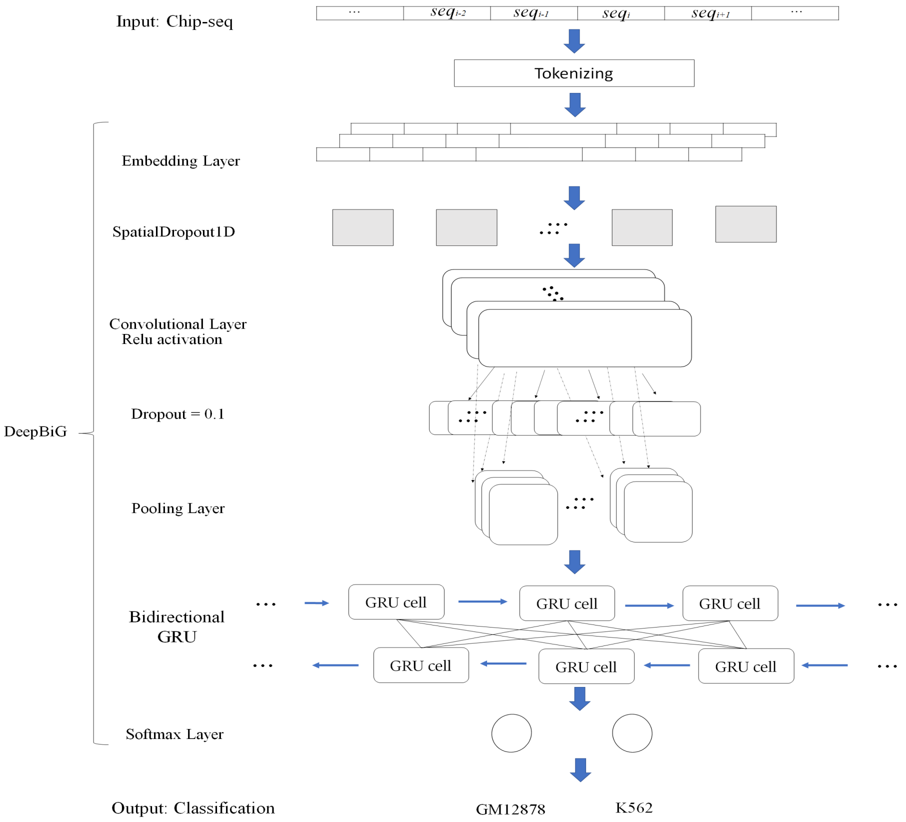

Fig. 1. Proposed Model - DeepBiG.

4) F1-Score: F1-score refers to seek for balance of the precision and recall. As shown in Eq. 8 [34], F1-score measures is there any uneven class distribution.

$$F1 - Score(F1) = \frac{2 * P * R}{P + R} \tag{8}$$

V. Result and Discussion

The results and discussion consist tables of performance metric in percentage that include accuracy, precision, recall and F1-score as well as model training time in minutes. There are four types of performance metrics comparison: 1) The comparison k-mers spectra with each being tokenized before being trained based on DeepBiG. 2) The comparison performance metric with difference combination of activation functions. 3) The comparison performance metric with different types of models and classifiers. 4) The comparison performance metric with different datasets.

A. Performance Comparison with Different k-mers

Table III shows the performance metric for k-mers spectra to evaluate genome assemblies. Noted that Class 0 is GM12878 and Class 1 is K562. Time is model training time in minutes. There are 2-mers, 3-mers, 4-mers, 5-mers and 6-mers. The accuracy increases from 2-mers to 4-mers and decreases after 4-mers. The simulations show 4-mers outperforms compare with others k-mer spectra with only 63 minutes in model training and 82.90% accuracy in predicting the ChIP-seq either belong to GM12878 or K562. However, the F1-score, the weighted average of precision and recall for 3-mers is better with only 1% different between class 0 and class 1 compare with 4-mers with 2% difference. But, the training time for 3-mers is double compare with 4-mers.

TABLE III. Performance Results in Term of Accuracy, Precision, Recall and F1-score for DeepBiG Model

k-mers	Time	A (%)	Class	P(%)	R(%)	$F1$(%)
2	99	81.70	0	78	90	84
			1	87	73	79
3	133	82.70	0	85	81	83
			1	81	84	82
4	63	82.90	0	82	86	84
			1	84	80	82
5	91	79.60	0	82	78	80
			1	78	81	79
6	67	77.30	0	84	70	76
			1	72	86	78

Fig. 2 displays the accuracy and loss for 4-mers during the training and validation phases with the highest accuracy is 88.17% and 82.80%, respectively. Early stopping at epochs 8 as overfitting occurred. This is one of the limitation of the design but it provides better accuracy compare with other models or classifiers as shown in Table V. Therefore, 4-mers encoding DeepBiG is chosen for the remaining experiments.

B. Performance Comparison with Different Activation Functions

Table IV shows the simulation results for different combination activation functions like relu, softmax and tanh. These

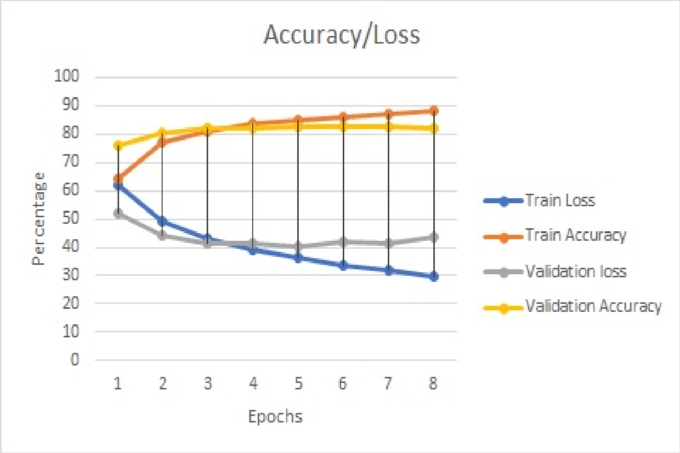

Fig. 2. DeepBiG using 4-mers, the training / validation's accuracy and loss.

activation functions are generally applied in deep learning models. The result shows that activation softmax for the last layer is preferable as it compatible with the adam optimizer and categorical cross-entropy loss. The accuracy for models where last layer is softmax activation is more than 80%. Relu and tanh are not suitable to be placed at last layer as vanishing gradient problem, in this simulation, class 0 is on higher side as the number of dataset is larger compares with class 1, then the gradient will be near zero. This has resulted no learning during backpropagation for class 1 as weights is updated with really small values. Noted that the simulation dataset for Class 0 is GM12878 and Class 1 is K562. Time is model training time in minutes.

DeepBiG is using relu activation at CNN layer and softmax activation at last layer. The performance in term of accuracy is higher almost 2% compares with relu and tanh activation in CNN layer. DeepBiG training time is double faster compares to softmax activation and 6 minutes quicker compares to tanh activation.

TABLE IV. Comparison Performance Results in Term of Accuracy, Precision, Recall and F1-score for Different Types of Models

Models	Time	A (%)	Class	P(%)	R(%)	$F1$(%)
Relu* - Softmax$^+$	63	82.90	0 1	82 84	86 80	84 82
Softmax* - Softmax$^+$	134	81.00	0 1	86 77	76 86	81 81
Tanh* - Softmax$^+$	76	80.60	0 1	81 80	81 80	81 80
Softmax* - Tahn$^+$	34	51.40	0 1	51 0	100 0	68 0
Softmax* - Relu$^+$	39	51.40	0 1	51 0	100 0	68 0
Relu* - Relu$^+$	34	51.40	0 1	51 0	100 0	68 0

C. Performance Comparison with Different Existing Predictors

Table V compares the performance in term of accuracy, precision, recall and F1-score between the deep learning models and machine learning classifiers. The dataset for Class 0 is GM12878 and Class 1 is K562. Time for these simulation is recorded in minutes. The deep learning models are bidirectional GRU (BiGRU), bidirectional long short-term memory (BiLSTM), CNN and the combination models. The machine learning classifiers are Naïve Bayes (NB), K-Nearest Neighbors Algorithm (KNN) and Random Forest (RF). Each method is simulated using the same dataset as stated and the dataset undergoes the pre-processing process as shown in Section II. The parameters for deep learning models are similar with DeepBiG which using dropout ratio of 0.1, kernel number is 5, cell number is 10, epochs is 15 and batch size is 64. The parameters for machine learning classifiers are varied for each others. NB smoothing parameter is set between the range of 0.1, 1, 10, 100 and 1000. In the KNN classification, the number of neighbors to be used in this simulation is in the range of 2, 5, 8, 10 and 15. For RF, the number of trees in the forest is set in the range of 10, 25, 30, 50, 100 and 200. The maximum depth of the tree is in the range of 2, 3, 5, 10 and 20. The minimum number of samples require to be at a leaf node is in the range of 5, 10, 20, 50, 100 and 200.

Deep learning models outperform compare to machine learning classifiers in term of accuracy, average is 80%. Machine learning classifiers' accuracy in average 55%. The result demonstrates the performance in term of accuracy of the proposed DeepBiG model is the highest (82.90%) by comparing with other models and classifiers on the same dataset. It follows by CNN + BiLSTM model with 81% accuracy. The training time for CNN is the only requires only 6 minutes but the accuracy below 80%. The weakest performance is NB classifier with best parameter 1000 achieves only 54.10% accuracy.

We noted overfitting with the symbol of *. The simulation dataset is long sequence with combination of nucleobases, A,C,G, and T. For each long ChiP-seq, it might contains some irrelevant DNA information related with the TF. We named it as noisy data. The models like DeepBiG, BiGRU, BiLSTM, CNN and CNN+BiLSTM learn the noisy within the training data. This has caused the overfitting. Hence, two solutions are provided to overcome the overfitting by adding dropout in the model and early stopping during training phase.

D. Performance Comparison with Different Size of Datasets

To further assess the performance of DeepBiG, we conduct experiments on four different combination TF datasets using DeepBiG and CNN+BiLISTM as shown in Table VI. The dataset include GM12878-ELK1, GM12878-SP1, K562-ARID3A and K562-CTCFL. Class 0 is GM12878 and Class 1 is K562. Simulation time is recorded in minutes.

Based on the results, we find that when the dataset size is smaller, the accuracy rate for DeepBiG is above 82.9%. If the dataset is smaller, the noisy decreases, this has resulted the increase of accuracy rate. Hence, this has proven there are noisy for the simulation dataset in Table V indirectly.

From Table VI, one may find that the DeepBiG predicts well when the dataset is larger compares to CNN+BiLSTM model. DeepBiG predictions accuracy for dataset EC, SA and SC are 87.90%, 84.10% and 89.40% respectively. CNN+BiLSTM model predictions accuracy for dataset EC, SA

TABLE V. COMPARISON PERFORMANCE RESULTS IN TERM OF ACCURACY, PRECISION, RECALL AND F1-SCORE FOR DIFFERENT TYPES OF MODELS AND CLASSIFIERS

Models/Classifiers	Time	A (%)	Class	P(%)	R(%)	$F1$(%)
*DeepBiG	63	82.90	0	82	86	84
			1	84	80	82
*BiGRU	360	78.10	0	84	71	77
			1	73	86	79
*BiLSTM	628	80.30	0	80	83	81
			1	81	78	79
*CNN	6	79.20	0	80	79	80
			1	78	79	79
BiGRU+CNN	509	80.10	0	78	85	82
			1	82	75	78
BiLSTM+CNN	635	79.90	0	81	80	80
			1	79	80	79
*CNN+BiLSTM	99	81	0	87	74	80
			1	76	88	82
BiGRU+CNN+BiGRU	830	80.90	0	81	82	82
			1	81	79	80
BiLSTM+CNN+BiLSTM	1244	80.70	0	78	88	82
			1	85	73	79
BiGRU+CNN+BiLSTM	978	80.70	0	81	82	81
			1	80	79	80
BiLSTM+CNN+BiGRU	1261	79.60	0	77	86	81
			1	83	73	78
NB	34	54.10	0	56	56	56
			1	52	52	52
KNN	1826	57.10	0	58	60	59
			1	56	54	55
RF	291	61.90	0	61	74	67
			1	64	50	56

and SC are 87.40%, 83.80% and 88.80% respectively. DeepBiG has 0.5% more accurate compares to CNN+BiLSTM. But, for dataset EA with total 14610 labelled data, the prediction accuracy for DeepBiG is 0.5% less than CNN+BiLSTM. However, the overall training time for DeepBiG is faster compares to CNN+BiLSTM.

TABLE VI. PERFORMANCE RESULTS IN TERM OF ACCURACY, PRECISION, RECALL AND F1-SCORE FOR DEEPBIG MODEL AND CNN+BILSTM WITH DIFFERENT DATASETS

Models	Time	A (%)	Class	P(%)	R(%)	$F1$(%)
DeepBiG-EA[1]	26	84.80	0	78	78	78
			1	88	88	88
DeepBiG-EC[2]	37	87.90	0	82	76	79
			1	90	93	92
DeepBiG-SA[3]	32	84.10	0	86	91	88
			1	80	72	76
DeepBiG-SC[4]	53	89.40	0	91	92	91
			1	87	86	87
CNN+BiLSTM-EA[1]	71	85.30	0	81	76	78
			1	87	90	89
CNN+BiLSTM-EC[2]	57	87.40	0	77	83	79
			1	92	89	91
CNN+BiLSTM-SA[3]	62	83.80	0	85	92	88
			1	82	69	75
CNN+BiLSTM-SC[4]	105	88.80	0	93	88	90
			1	84	89	87

EA - GM12878-ELK1 and K562-ARID3A with total dataset 14610.[1] . EC - GM12878-ELK1 and K562-CTCFL with total dataset 17117.[2] . SA - GM12878-SP1 and K562-ARID3A with total dataset 27274.[3] . SC - GM12878-SP1 and K562-CTCFL with total dataset 29781.[4]

VI. CONCLUSION AND FUTURE WORK

In this paper, the combination of k-mers encoding with tokenizing have been introduced for the data pre-processing phase. In the experiments, the DNA sequences are sized from 2-mers up to 6-mers are considered. The hybrid deep learning algorithms, we named it as DeepBiG is proposed with combination of CNN and BiGRU. DeepBiG is simulated and is analysed in terms of training time, accuracy, precision, recall and F1-score. The results reveal that the proposed 4-mers encoding DeepBiG gives better accuracy with 82.90% when compares with other deep learning models and machine learning classifiers. Although our model achieves better result, there is a limitation of DeepBiG is overfitting. Therefore, dropout and early stopping is adding into the model. There are open researches for improving this model which may still preserve the accuracy during learning, validation and prediction phases. For example, noise deduction during data pre-processing and reduces overfitting at model training phase.

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Actor Critic-based Multi Objective Reinforcement Learning for Multi Access Edge Computing

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***Abstract*—In recent times, large applications that need near real-time processing are increasingly being used on devices with limited resources. Multi access edge computing is a computing paradigm that provides a solution to this problem by placing servers as close to resource constrained devices as possible. However, the edge device must consider multiple conflicting objectives, viz., energy consumption, latency, task drop rate and quality of experience. Many previous approaches optimize on only one objective or a fixed linear combination of multiple objectives. These approaches don't ensure best performance for applications that run on edge servers, as there is no guarantee that the solution obtained by these approaches lies on the pareto-front. In this work, Multi Objective Reinforcement Learning with Actor-Critic model is proposed to optimize the drop rate, latency and energy consumption parameters during offloading decision. The model is compared with MORL-Tabular, MORL-Deep Q Network and MORL-Double Deep Q Network models. The proposed model outperforms all the other models in terms of drop rate and latency.**

Keywords—Edge computing; reinforcement learning; multi objective optimization; neural networks; deep learning

I. Introduction

In the modern day, mobile devices handle more computationally demanding activities, including data processing, artificial intelligence, and virtual reality. Despite advancements in mobile technology, these devices lack sufficient computational capacity to complete all of their duties locally with low latency and reasonable energy consumption. Mobile apps for online gaming, signal or image processing (such as facial recognition), augmented reality, and real-time translation services are some examples of computational domains whose use has grown drastically that places a substantial computing demand on mobile devices (MDs) which have a limited amount of resources.

Mobile edge computing (MEC), also known as fog computing and multi-access edge computing, is a technology that enables effective job processing. [1] It is a new computing paradigm in which computing, network, storage, capabilities are migrated to edge nodes, which is closer to end-users to meet real-time needs of fast changing IT industries. The demand for on-demand computation close to mobile devices is only expected to grow. Additionally, as 5G networks become more and more popular, the three main services - massive machine communication, enhanced mobile broadband and ultra-reliable low-latency communication pose network, computing, storage, and application core capabilities. As a result, their applications can be run on the edge server, enabling faster network service response and satisfying the real-time processing, intelligent application, security, and other requirements. Despite edge computing's enormous potential, there are many obstacles. Mobile real-time apps are extremely sensitive to latency and power usage. However, the prolonged time of execution of these applications can result in excessive energy consumption owing to the randomness and volatility of mobile edge networks.

Single objective reinforcement learning algorithms perform considerably well in environments where there is only one objective to optimize, which is often not the case in real world scenarios. The offloading requirement in the case of multi-access edge computing needs to satisfy many conflicting requirements like latency, energy, drop rate, QoS, and cost, among others. Optimization of just one objective can provide neither a guarantee of pareto optimality nor a control over the order of preference of the multiple objectives to suit the specific use-case, albeit at the cost of pareto optimality. Multi objective reinforcement learning (MORL) approaches can be leveraged to overcome the above shortcomings whilst maintaining adaptability to work in dynamic environments.

The research contribution of this work is the application of the actor critic method in multi objective reinforcement learning algorithms for the task offloading problem as opposed to previous literature that have used the actor critic method for single objective reinforcement learning.

II. Related Work

The decision to offload a task or not is a complex one, with multiple factors about the problem itself and the solution to be considered. Firstly, tasks can be considered to either be dependent or independent of one another. Literatures choosing to work on dependent tasks usually consider a directed acyclic graph to represent task dependencies. Secondly, the decision to offload or not can be made either centrally or by each mobile device, in a decentralized fashion. We have considered the papers that have used reinforcement learning to make the decision to offload or not. The network architecture of mobile devices and servers must be considered. The parameters for making the decision to offload or not are the task size, algorithmic complexity, the time by which the task needs to be completed, task interdependencies, and bandwidth. Authors choose a subset of these parameters for their system. The RL system can either be based on table or on function approximation. The reward for the RL agent can be based on latency, energy, cost, drop rate, QoS considerations.

Tang et al. [2] propose a cost optimized reinforcement learning algorithm, where every mobile device makes an independent decision to offload or not, while also being aware of edge load dynamics. T Alfaikh et al. [3] propose using SARSA for making the decision to offload or not to the closest server or adjacent server or to compute it locally. J Wang et al. [4] propose using meta RL for faster adaptability and use a sequence2sequence network for making the decision to offload or not. J Wang et al. [5] combine their approach with a specific off-policy policy gradient algorithm with a clipped surrogate objective. Liang Huang et al. [6] propose using deep q learning while optimizing on energy with constraints on bandwidth. Peizhi Yan et al. [7] propose using deep q learning with both node and edge level offloading. Xiaowei Liu et al. [8] propose using a parameterized, indexed-value function for value estimation for achieving faster convergence.

Zhenjiang Zhang et al. have proposed a multi-agent load balancing distribution deep reinforcement learning algorithm [9]. It minimizes the latency, load factor and the algorithm complexity as compared to a centralized algorithm. It uses a genetic algorithm to identify the decision to offload or not while still meeting the QoS requirements of all the tasks. Yu Dai et al. propose a federated reinforcement learning algorithm to address the issue of weak generalization of the model and privacy leakage caused by sharing user sensitive information to the central server [10]. Attention is used to aggregate the parameter weights resulting in the reduction of the processing time of the task. Yuanchao Xu et al. [11] explore decentralized multi-agent reinforcement learning algorithms to solve the problem of task offloading accounting for reward uncertainty. They try different approaches like Multi-Agent Deep-Deterministic Policy-Gradient (MADDPG), Robust MADDPG and Decentralized Partially-Observable Markov Decision Process (Dec-POMDP). Baris Yamansavascilar et al. [12] propose a task orchestrator based on deep reinforcement learning which learns to satisfy different task requirements without any human interaction. The problem is modeled as a Markov decision process and the Double Deep Q-Network algorithm is used to minimize the task drop rate. Xiangjun Zhang et al.[13] propose a task offloading algorithm for Reconfigurable Intelligent Surface (RIS) empowered Mobile Edge Computing networks. The problem is formulated as a Markov Decision Process (MDP) where latency, energy consumption and operating costs are minimized. DDPG is used to jointly optimize the phase shift and amplitude of RIS, task allocation strategy and offloading decision. Tu et al. [14] design a predictive offloading algorithm that makes use of deep RL and long short-term memory (LSTM) networks. The MEC server's load is monitored and the next task is predicted using the LSTM network. The amount of latency, energy used, and work abandonment is decreased. Liang Huang et al [15] propose an online, deep RL based algorithm to adapt task offloading and resource allocation decisions to the time varying wireless channel conditions. They aim to minimize the latency. Mingjie Feng et al. [16] explore offloading of tasks between MEC servers and cloud servers using DRL. They aim to minimize average latency and achieve optimization in task partitioning ratio and cloud selection.

Yi Ouyang et al. propose a task offloading algorithm for a vehicle edge computing environment based on Dueling-DQN [17]. The proposed approach considers the mobility of the vehicles and the changing network conditions make a better decision to offload or not. The results of the experiment demonstrate the effectiveness and superiority of the proposed algorithm with respect to existing approaches. Fuhong Song et al. have proposed an approach which uses multi-objective reinforcement learning for optimizing the UAV's trajectory and offloading decisions in real-time [18]. The algorithm considers multiple objectives, including minimizing energy consumption, maximizing data processing efficiency while maintaining a stable network connection. Xianfu Chen et al. propose a new approach based on deep reinforcement learning which optimizes performance of offloading algorithms in virtual edge computing systems [19]. Unlike other approaches which use traditional heuristics or machine learning algorithms, the proposed approach uses a deep-neural network to learn the optimal offloading policy in a data-driven manner. Junyao Yang et al. [20] propose an inverse order based optimization technique for resource allocation and task offloading in multi-access edge computing systems. It makes the offloading decision and resource allocation and optimizes them jointly using an inverse order optimization strategy unlike other approaches which consider them separately. Ting Wang et al. [21] propose an approach based on deep reinforcement learning (DRL) for improving the performance of task offloading in the Internet of Vehicles (IoV) scenario. The proposed approach uses a deep neural network to learn the optimal offloading policy based on IoV's dynamic and uncertain environment. Hongxia Zhang et al. [22] propose an ultra-low latency multi-task offloading approach for making task offloading decisions in mobile edge computing that considers multiple tasks with different requirements, such as computation, communication, and storage. The proposed approach uses a multi-agent reinforcement learning algorithm to make the decision to offload or not while satisfying the different task requirements. X Zhang et al. [23] propose an approach based on deep reinforcement learning for energy-efficient task offloading in secondary mobile edge systems. The proposed approach uses a deep-neural network to learn the optimal offloading policy in accordance with the dynamic and uncertain environment of the edge system. Mushu Li et al. [24] propose creating a cooperative edge computing framework to lower latency and increase dependability for vehicular networks. In order to determine the best option that reduces the cost of the service, a DDPG algorithm is used.

Juan Chen et al. [25] propose a multi-agent DRL solution to minimize total cost in terms of energy requirement of IOT device and long term renting cloud costs. They have explored centralized training and decentralized execution, hence, each IOT device will be a decision making agent. Xing Chen et al. [26] explore a federated DDPG solution for combined optimization of energy consumption and reduction in latency. The federated learning procedure ensures privacy of user data because only parameters of locally trained models are sent to central servers. Hao Meng et al. [27] constructs a DRL model with a new reward function design for optimizing the battery power of mobile devices. The reward function simulates the tradeoff between latency and battery consumption. Kun Wang et al. [28] formulated a Double DQN model to apply the task offloading concept to the Internet of Vehicles. This proposed algorithm solves real-time changes in the network due to user movement. Fuhong Song et al. propose a MORL algorithm to make the decisions with respect to task offloading when subject to multiple dependent tasks to optimize on three objectives, energy consumption, latency and user costs, simultaneously and using independent rewards for each [29]. They use tournament selection schemes to maintain previously learnt policies. Yu Chen et al. [30] investigated multi-user edge video analytics task offloading problems. The authors design two algorithms, one based on Game Theory and another based on the Actor-Critic method. The proposed A2C is observed to be more flexible, users can adjust accuracy decisions and achieve the converged reward.

III. MEC ARCHITECTURE

The considered architecture shown in Fig. 1 is similar to [2] where there is a set of resource constrained mobile devices M = {1, 2, 3, …. , m} and a single edge server in the MEC environment. We measure time using discrete timesteps where each timestep is equal to 100 milliseconds. All mobile devices are polled at the start of each timestep to check if any tasks have been generated. The following section explains the device and server models.

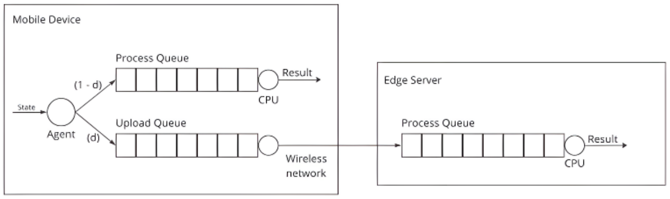

Fig. 1. MEC architecture

A. Device Model

The test environment consists of multiple mobile devices which generate non-divisible tasks with no interdependency which can either be computed locally on the device or on an edge server. Tasks can only be generated at the start of each timestep. The decision d as to whether a task has to be computed locally on the resource constrained mobile device or offloaded to an edge server is taken by a reinforcement learning (RL) agent. If the task has to be computed locally, it is first pushed into the local process queue of the device. The process queue follows a first-in first-out (FIFO) principle and once the task is computed, its result is returned. If the task is supposed to be offloaded, it is pushed into the upload queue of the device and subsequently uploaded to the edge server. Similar to the process queue, the upload queue follows a FIFO principle. It is assumed that once a task is computed or uploaded, the computation or upload process of the next task in the respective queue will be started only in the next timestep.

1) Task model: It is assumed that new tasks are only generated at the start of each timestep. Tasks are generated in all mobile devices with a probability of 0.3. For each task the parameters considered are, the task size (in bits), task timeout (in timesteps), algorithmic complexity and start time of the task. The task start time is the timestep at which the task was generated. In case a task is computed locally, the total execution time is equal to the sum of the duration of time spent in the process queue of the device and the actual computation time. Otherwise, if it is offloaded, the total execution is equal to the sum of the duration of time spent in the upload queue of the device, the time necessary to upload the task to the edge server, the duration of time spent in the process queue of the edge server and the time necessary to execute the task on the edge server. Each task has an associated timeout and if the task is not executed within the timeout, it is considered to be dropped.

2) Offloading decision: The Agent A makes the decision to offload or not d, depending on the state which contains the task timeout, task size, the time required to upload the task, time required to execute the task on the server and the local execution time of the task. d is a binary variable d {0, 1} where d is 1 if the task is to be offloaded or 0 if it is to be processed locally. As seen in Fig. 1, if d is 1 it is pushed into the upload queue of the device, else it is pushed into the local process queue of the device.

B. Edge Server Model

A single edge server is considered in our MEC environment. Tasks which are uploaded to the edge server are pushed into the process queue of the server only at the start of a time step. Before a task is pushed into the process queue of the server, we check if the task is going to be dropped, i.e, it is checked if the task has no possibility of getting executed within its timeout and if so, the task is considered to be dropped and the task will not be pushed into the process queue of the server. The tasks in the queue are computed in a First-In First-Out order. Instead of having one process queue for each mobile device, we maintain a single process queue for all devices. This has the same effect as having a process queue for each device and a First-In First-Out scheduler to pick tasks from all the queues.

C. Reinforcement Learning Environment

We consider a single edge server connected to multiple resource constrained mobile devices via a wireless network.

1) State space: State space is essentially the input to the RL agent to make the task offloading decision. It is a vector of task size, algorithmic complexity and the time before which the task must be processed.

2) Action space: Action space is the set of values that can be returned by the agent. The agent makes a binary decision (0 or 1) i.e. to offload or not.

IV. MULTI OBJECTIVE REINFORCEMENT LEARNING

Multi objective reinforcement learning is a type of reinforcement learning that aims to optimize multiple potentially conflicting objectives simultaneously to achieve ideal performance in real world scenarios. The architecture explained in the previous section is used to compare four multi-objective reinforcement learning algorithms in a simulated environment containing ten resource constrained mobile devices connected to a single edge server.

A. Actor Critic Method

The actor-critic method is a popular temporal difference (TD) learning approach that consists of two main components, the actor and the critic. The actor suggests actions that can be taken based on a particular state and the critic evaluates the actions taken after being suggested by the actor. Four neural networks are considered namely, actor, critic, actor-target and critic-target. The actor network outputs the expected Q value for each action and the action which has the highest expected Q value is chosen as the next action to be taken. The critic network is used to evaluate how good the action suggested by the actor network is. In addition to the state, the critic network also takes the action taken and the reward obtained as the input. Then, the loss is computed for both the actor and the critic networks and update them.

The actor-target and critic-target networks are used to stabilize the training of the actor and critic networks. At the end of each timestep the network parameters are partially copied from the main networks to the target networks via soft updates. Experience replay is used every 25 timesteps to effectively train the model. This algorithm outperforms all the previous algorithms with respect to drop rate and latency.

Algorithm 1: Actor-Critic method for task offloading

```
Params: Learning rate $\alpha \in [0, 1)$, small epsilon $\varepsilon$, $0 < \varepsilon < 1$, convergence parameter $\gamma$ close to 1
Initialize networks $Q_a$ , $Q_a$`, $Q_c$ and $Q_c$`
foreach timestep with task do
    select action a from the set of possible actions A
    using policy derived from $Q_a$`($\varepsilon$-greedy);
    if a is offload:
        add task to upload_queue at mobile device
    elseif a is local_computation:
        add task to process_queue of the respective mobile device
    observe reward R, next state s`;
    store the experience (s, a, R, s`) in replay-buffer
    $Q^*(s, a) = R + \gamma \max Q_c`(s, a)$
    compute mean squared error between $Q_c(s, a)$ and $Q^*(s, a)$, update critic network
    update actor network using loss$\leftarrow \frac{1}{N} \boldsymbol{\Sigma}_i Q_c (s_i , \max Q_a(s_i, a))$
    update target networks
        $\theta_a` \leftarrow \tau \theta_a + (1 - \tau) \theta_a`$
        $\theta_c` \leftarrow \tau \theta_c + (1 - \tau) \theta_c`$
    $s \leftarrow s`$
    use experience replay to train the actor and critic networks every 25 timesteps
end foreach
```

B. Objectives

The multi objective reinforcement learning model aims to optimize three objectives namely, the task drop rate, latency and the energy consumed by the device.

Task drop rate: The task drop rate is the number of tasks dropped until the current timestep divided by the total number of tasks that were generated until the current timestep.

Latency: Latency is the duration of time between task generation and task completion.

latency = d * (upload_latency + process_latency_server) + (1 - d) * (process_latency_device)

where,

d is the decision to offload or not which takes a binary value (0 or 1)

upload_latency is the total timesteps required to upload the task

process_latency_server is the total timesteps which the server takes to execute the task taking into account the server load (time spent by the task in the process queue of the server)

process_latency_device is the total timesteps taken by the mobile device to execute the task considering the time spent by the task in the process queue of the device.

Energy: It is the energy utilized by the mobile device from the moment the task is generated on it, to the moment the task is completely processed. Naturally, offloaded tasks use a lot less energy than the tasks that are processed locally.

energy = d * (latency * idle_energy_rate) + (1 - d) * (latency * active_energy_rate)

where,

idle_energy_rate is the energy utilized by the device in its idle state

active_energy_rate is the energy utilized by the device during execution

Single objective optimization usually comes at the expense of other objectives which might make the solution not feasible for a lot of real-world applications where we often need to jointly optimize multiple objectives. Multi objective reinforcement algorithms are handy in such scenarios.

C. Reward Engineering

The reinforcement learning agent is given some reward as a result of every action it takes. It gets a positive reward if it takes an action that contributes towards optimization of the objective, otherwise it is punished with a negative reward.

When it comes to multi-objective reinforcement learning where the model optimizes the task drop rate, energy and latency, three rewards need to be considered.

1) A reward of +1 is given to the agent if the task gets executed successfully within its timeout, else it is given a reward of -1. A task is considered to be dropped if it cannot be executed within the timeout specified for that particular task.

2) With regard to energy, we consider a threshold of 0.5 mJ if the task is offloaded and 160 mJ if the task is computed locally. This difference is due to the fact that when a task is offloaded, the mobile device consumes energy only to offload the task and not execute it. The agent gets a reward of +1 if the energy consumed for the given task is below the threshold, otherwise it gets -1 as the reward.

3) Similarly, if the latency for the given task is below 2000 ms, the agent gets a reward of +1, else -1.

The establishment of these thresholds was the outcome of experimentation. It was observed that the average amount of energy consumed per task and the average latency over a period of time for the given task parameters were 0.5 mJ / 160 mJ and 2000 ms respectively in our simulation environment. The three rewards are combined using a set of weights that add up to 1 to obtain a single total reward that is utilized to train the multi-objective reinforcement learning agent. The weights can be changed accordingly if a particular objective is required to have a higher priority than other objectives.

V. Experiments

The experiment was run with different models with tasks generated at the mobile devices with a probability of 0.3 at each timestep. The model under training makes the decision as to either offload the task or to process it locally. The task is appended to the respective mobile devices' upload queue if it is to be offloaded. If the task is to be computed locally, the task is appended to the local computation queue of the mobile device. The experiment is run with ten mobile devices and one edge server for 10,000 tasks. The latency, energy and drop rate is monitored and recorded during the experiment.

VI. Experimental Results

The MEC environment is simulated with ten resource constrained mobile devices and one edge server. We implemented and compared four multi objective optimization algorithms in the same environment with uniform random policy, which is a standard benchmark for any RL model. All the multi objective reinforcement learning models aim to optimize the task drop rate, energy and latency.

We compare the performance of the MORL Actor-Critic model with three other MORL models.

1) MORL-Tabular: We apply the Tabular Q learning algorithm to make the task offloading decision in our MEC system. We consider the four parameters task size, algorithmic complexity, timeout in timesteps and store the action-value pair in a table. In each iteration, the Q-learning model refers to the previous action-value pairs from the table and based on the bellman equation for each update the new action-value pair. Tabular Q Learning can be used for solving problems where the number of states is not large as the storage is limited. Once the problem size increases, we cannot scale Tabular Q Learning, especially in environments where the state space has continuous values.

2) MORL-DQN: We implemented the Deep Q Learning algorithm where, instead of a table we make use of a neural network to map a particular state to an action value, i.e the neural network takes the current state as the input and we get the expected Q value as the output. The action which has the highest Q value stands as the most optimal choice for the present state. We consider the task size, task timeout, time taken to upload the task, time taken to compute the task on the server and time taken to complete the task on the mobile device to make the decision as to whether the particular task at hand should be offloaded to the MEC server.

3) MORL-DDQN: Although Deep Q Learning algorithms perform well, there exists a maximization bias. If at any point in time the Q value is overestimated, the error gets compounded overtime and leads to suboptimal policies and poor exploration. To overcome this issue, in Double Deep Q Learning, two neural networks are used instead of one. We assume one network as the target Q network which is updated less frequently and is used to calculate the target Q values for the Q value update of the other neural network called the online network. The online network is used to determine the best known action in a particular state. The weights of the online network are copied to the target network intermittently.

B. Cumulative Reward

In MORL, a positive reward is given to the model for not just executing the task successfully but also if the task is executed within a limited latency and limited battery utilization of the edge device. A negative reward is given if the task is dropped or if the task is not executed within the thresholds of energy or latency. Fig. 2 shows the plot of cumulative reward vs. timesteps. Although, an analysis is necessary, it is unreasonable to infer the comparison of agent performance from this plot alone.

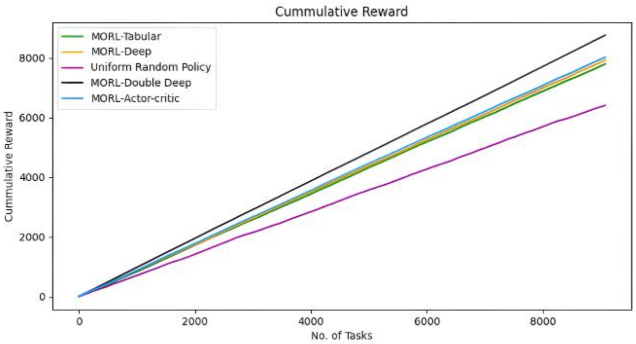

Fig. 2. Cumulative reward of different models.

C. Drop Rate

The crucial factor to adjudicate the performance is the total tasks dropped as a result of the decision made by the models. Each task has a timeout within which the task must be executed, otherwise, it is considered to be dropped. At each timestep we calculate the number of dropped tasks. This factor can be used to consider the task offloading problem as a minimization problem. Fig. 3 shows that uniform random policy drops a significant number of tasks. Deep MORL models, on the other hand, have the running task drop rate close to zero. The MORL actor critic model not only decreases the drop rate but also improves the stability of its output compared to both DQN models.

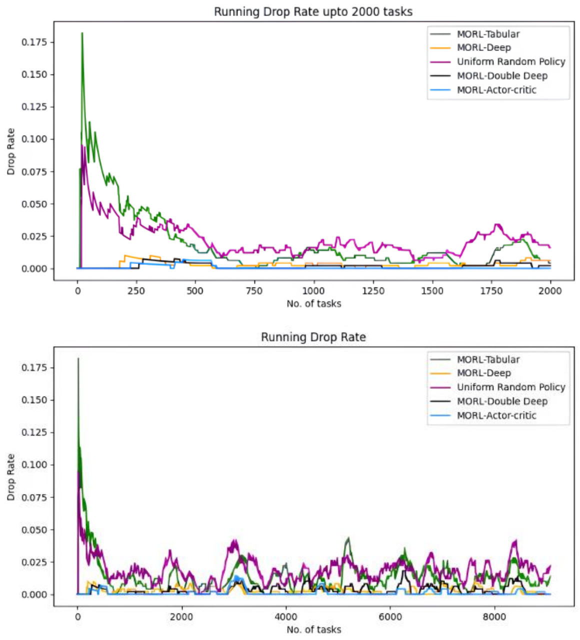

Fig. 3. Running drop rate of tasks.

D. Latency

The second most important factor to adjudicate the performance of our models is how quickly we are able to execute all the tasks. The agent gets a positive reward if a task is executed within the latency threshold or else it gets a negative reward. From Fig. 4, it can be seen that the MORL-DQN model performs considerably well compared to the tabular MORL model and uniform random policy. The MORL actor critic model estimates and optimizes the latency significantly compared to the other approaches.

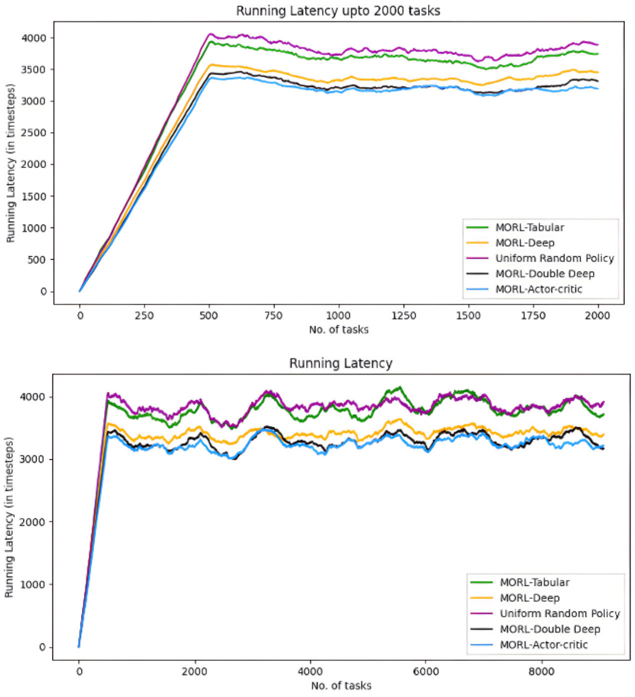

Fig. 4. Running latency of execution of tasks.

E. Energy

Another important factor to consider is the battery consumption to process the tasks at the edge device. This factor allows the model to take into consideration that we intend to minimize the battery utilization of the edge device. Hence the decision made by MORL is not just influenced by latency or drop rate but also by battery consumption. We have set a threshold for each device and if a task is going to get executed locally, we want those tasks to be executed within this threshold. In such cases, we provide the agent with a positive reward and if any task's execution crosses the threshold, we provide the agent with a negative reward.

From Fig. 5, it is observed that the Deep MORL model does considerably well compared to all the other models. The tabular MORL model performs quite well but doesn't provide the same stability that the deep MORL model gives. It is true that MORL actor-critic leads to a greater amount of energy consumption on average than other approaches, but it is due to the fact that more tasks are executed on the mobile device as compared to other algorithms to achieve better drop rate and latency. It shows a greater degree of stability compared and better overall performance on all objectives.

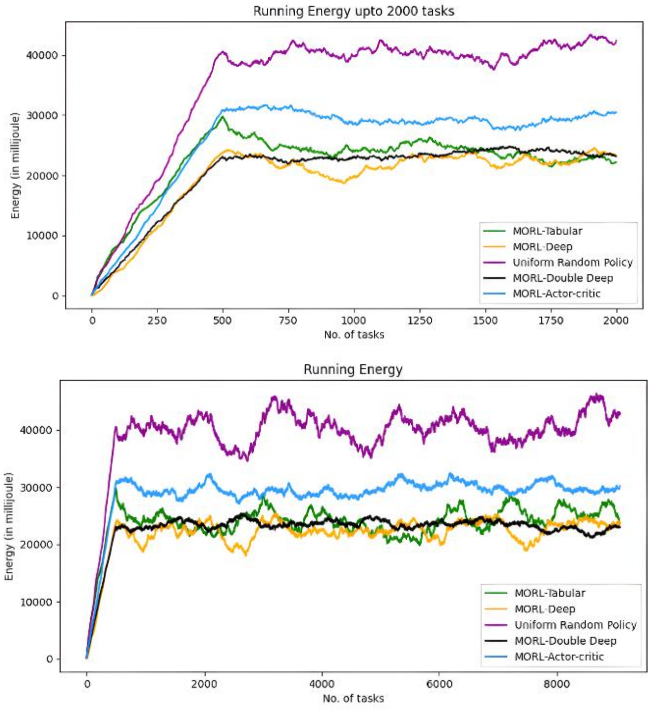

Fig. 5. Running energy consumed by the edge device.

F. Comparison

Table I provides a comparison of the results obtained when all algorithms were applied to 3000 episodes using 10 edge devices connected to a single MEC server. All edge devices generated a total of 9073 tasks.

G. Benefits of Multi-objective Optimization over Single-objective Optimization

Single objective approaches seem to outperform the multi objective ones on the objective which they have been trained to optimize. However, a closer look into the performance of all objectives will reveal the obvious superiority of multi-objective reinforcement learning approaches. To better understand the aforementioned claim, we compare a SORL model [31] which optimizes energy consumption and the MORL actor-critic model.

TABLE I. RESULT EVALUATION TABLE

	Objectives			**Decisions**	
Model	Net Drop Rate	Mean Latency (in timesteps)	Mean Energy consumerd (in mJ)	Offload	Local
MORL-Tabular	0.0406	22.963	147.5110	5891	3182
MORL-DQN	0.0083	20.690	**136.1579**	6304	2769
MORL-DDQN	0.0081	19.853	140.6437	5187	3886
MORL-Actor Critic	**0.0034**	**19.62**	179.6439	4861	4212
Uniform Random Policy	0.0590	23.521	248.1667	4515	4558

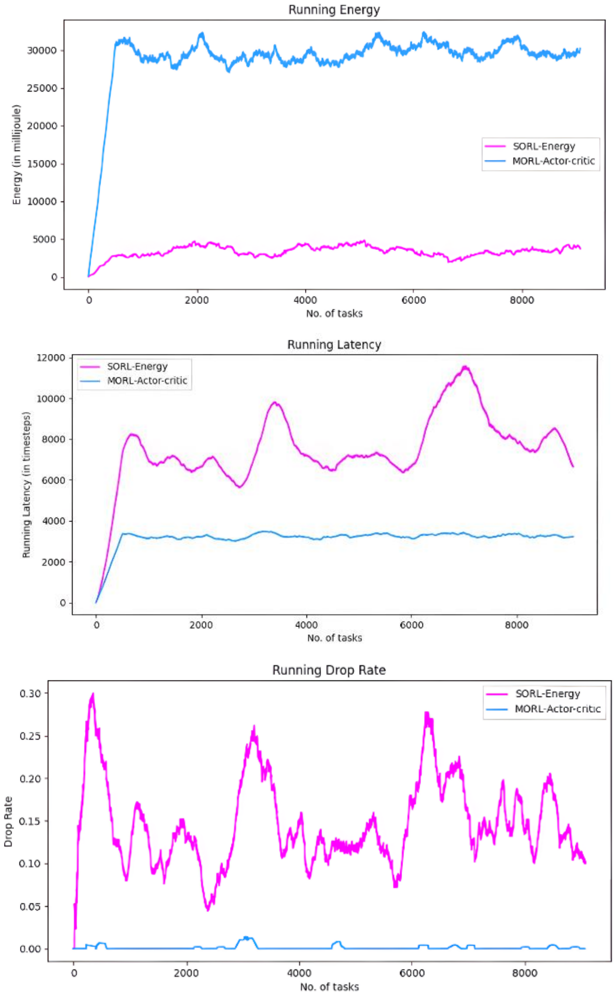

Fig. 6. Comparison of objectives' performance using single-objective and multi-objective optimization techniques.

Fig. 6 shows that the SORL model performs exceptionally well in terms of the objective that it optimizes, i.e, energy consumed. It offloads most of the tasks to the edge server to cut down on the energy consumption. However, this comes at a cost of drop rate and latency. The drop rate and latency achieved by the SORL model is unacceptable in real world applications, whereas the MORL actor-critic model optimizes all three objectives reasonably well which makes it more practical.

We conclude with the observation that the agent trained using the MORL actor critic method exhibited the best overall performance.

VII. CONCLUSION

Multi-access Edge Computing (MEC) tries to improve user experience and reduce energy consumption. It is a popular and emerging paradigm that takes the cloud closer to resource constrained mobile devices. A general scenario depicting the interaction between a few mobile devices and a MEC Server is simulated in which four multi-objective reinforcement learning algorithms are compared. From the results observed, we can conclude that multi-objective reinforcement learning based actor critic model outperforms other models in terms of both latency as well as task drop rate.

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A Review on Applications of Electroencephalogram: Includes Imagined Speech

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***Abstract*—In the last two decades, the Brain-Computer Interface system with EEG signals has assisted people in various ways. In particular, to patients with paralysis, epilepsy, and Alzheimer's disease, not only to the patient but also to physically, visually challenged people and Hard-of-Hearing people. One of the non-invasive methods that can read human brain activities is Electroencephalogram (EEG). The EEG has been used in many applications, especially in medicine. The applications of the EEG are not limited to the medical domain; it keeps extending to many areas. This review includes the various application of EEG; and more in imagined speech. The main objective of this survey is to know about imagined speech, and perhaps to some extent, will be useful future direction in decoding imagined speech. Imagined speech classifications have used different models; the models are discussed, the significance of choosing the number of electrodes, and the main challenges in EEG.**

Keywords—Electroencephalogram; brain signals; invasive; non-invasive; imagined speech; electrodes; epilepsy

I. Introduction

Speaking, hearing, seeing, and moving are all necessary to humans. However, few people are having issues with that, either by birth or due to illness. They could not lead an everyday life. However, technology and science can provide some alternatives for them. Artificial Intelligence (AI) and Brain-computer Interface (BCI) [1] are considerable gifts to them to lead a better life. The Brain-Computer interface system introduced during the year 1973 by Jacques Vidal. It converts the human brain signals into instructions for the computer [2].

In the last two decades, Brain-Computer Interface had a vital role in the field of the medical domain. In particular, for those who have paralyzed, have a seizure problem, have a brain disorder, have speech problems, have hard of hearing, and so on., it has given confidence to them in assisting in many ways. Specifically, they are not necessary to depend on others. A fully paralyzed person has motor issues, eyeballs that will not move, and articulation problems. They cannot communicate in any other technique except brain wave with the BCI system [3] because, cognitively, they are normal. Invasive and non-invasive methods are available to read brain signals. Many researchers have used these methods, but for the practical approach, non-invasive is more suitable rather than invasive. Complete details were in the other sections of this systematic review. Imagined speech, covert speech, inner speech, and intended speech are new paradigms for researchers. No phonetic sounds, but tongue and jaw movements will be present are refers as silent speech. Imagined speech is akin to silent speech, but tongue and jaw movements will not be present; a person should be in verbal thinking [4].

As per Proix et al., non-invasive methods have not given convincing results and have limited success due to brain signals taken on the scalp by either EEG or MEG technique during the imagined speech; brain signals are weak and vary with overt speech [5]. Instead of non-invasive, Proix et al. used invasive techniques. Many researchers have applied Machine learning or Deep learning algorithm to decode imagined speech using non-invasive.

The deep learning method required massive data to train the model for good accuracy [6]. This systematic review includes details of the few machines learning algorithm and the deep learning algorithm applied in decoding EEG signals by the researchers. Reddy et al. proposed Hamilton-Jacobi-Bellman (HJB) equation to get an optimal update rule for training Feed Forward Neural Network (FFNN); in this, the author achieved faster convergence and better performance [7].

In any BCI application, the brain signal controls the system. BCI system is composed of four different phases. Signal Acquisition, Feature extraction, classification, and device output [8]. Reading electrical activity of the brain is called signal acquisition. Different modalities are available to acquire the signals in the brain; EEG is one of the modalities. The details have given in the following section. Feature extraction is a method of analyzing the signal as per the application. Assign a label to the extracted feature in the classification result; this will enable specific control commands like cursor control, robotic arm movement, and user feedback. Thus, it closes the loop [8, 9]. Before performing all these, people must know about the human brain.

II. Brain Anatomy

The human brain has divided into two different portions: the cerebellum, a smaller portion, and the cerebral/cortex, a large portion of the brain. The brain's cortex area has divided into four different lobes: frontal lobe, parietal lobe, temporal lobe, and occipital lobe, respectively. Each lobe has its function. The frontal lobe is associated with cognitive function, speech, and short-term memory.

The responsibility of the parietal lobe is to have senses like smell, taste, and touch. The temporal lobe is associated with the hearing and memory process. The occipital lobe recognizes color and visual processes. Broca's and Wernicke's are associated with speech and language [10].

A. Brain Signals

The brain generates the electrical activity of the brain signals. During the electrical activity, electrochemical signals pass through the entire brain region with oscillation; they are called brain signals [11]. Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ) are the five different brain signals generated in the human brain [12]. Details of brain signal's frequency and its associated characteristics are provided in Table I.

TABLE I. CHARACTERISTICS OF THE BRAIN WAVE

Frequency Band	Frequency in Hz	Brain states	Originating place
Delta (δ)	0.5 - 4	Sleep	Frontal lobe
Theta(θ)	4 -8	Deeply relaxed	Temporal lobe
Alpha(α)	8 - 12	Very relaxed, eyes are closed	Frontal lobe & Occipital lobe
Beta(β)	12 - 35	Active, high awareness, and eyes open	Frontal lobe & central
Gamma(γ)	Above 35	Full concentration	Frontal, Temporal, and Parietal Lobes

B. Brain Signals Acquisition

There are two methods in the signal acquisition, namely Invasive and non-invasive methods. The first method required surgery to implant the electrodes in the brain's cortical area. The second one does not require implanting. Moreover, for research and practical purpose, it uses the non-invasive method. Its ease of use, cost-effectiveness, better accuracy, and reliability with the advancement of technology is why it prefers the non-invasive method [13]. Invasive type of electrode requires surgery to implant. Electroencephalography (ECoG) should place on the brain surface under the skull. ECoG provides electrical potential measured directly on the brain surface at a high spatial and temporal resolution without filtering the signals through the skull or scalp [14]. Intracortical electrodes are inserted in the cerebral cortex to record electrical signals. Any invasive electrodes have high spatial and temporal resolutions with the drawback of neuronal damage [15, 16]. Electroencephalography (EEG) Hans Berger recorded his first EEG in 1924. It is a non-invasive type [17]. Traditionally EEG is considered low spatial resolution but good at a temporal resolution [18]. A few researchers proved that the EEG is good at spatial resolution using surface Laplacian computation [19] and Tripolar Concentric Ring Electrodes [20] and combining EEG and fMRI to encode visual stimuli [21]. Magnetoencephalography (MEG) measures brain activity by the magnetic field generated by the electrical activity of the neurons. It provides high spatial and temporal resolution than the EEG [22, 23].

Functional Magnetic Imaging (fMRI) Clinical laboratories use Functional Magnetic Resonance Imaging (fMRI). When a particular brain area is active, that area will have more blood flow. fMRI finds the activity of the brain during changes in blood flow. The fMRI is good at spatial resolution and poor at a temporal resolution [24, 25]. Functional Near-infrared Spectroscopy (fNIRS) is a non-invasive brain signal acquisition device. Which is used widely in clinical applications like Parkinson's, Alzheimer's diseases, and childhood disorders could be diagnosed, and also it could be used in the Brain-computer interface. It emits less radiation, is user-friendly, has less cost, and is portable [26].

Among all non-invasive methods, EEG is the better option for researchers. Because of these reasons, easy to use, cost-effective, portable, and good at temporal resolution. In general, spatial resolution is low. However, it could enhance with Surface Laplacian computation [19] and Tripolar Concentric Ring electrodes [20] and more use of practical applications. 1 to 256 channels are available.

C. International Standard 10-20 EEG System

EEG signals are non-linear and highly non-static. The numbers 10 and 20 are the distance between adjacent electrodes. 10% and 20% of the total distance of the skull from the front to the back or left to right [26, 27]. Reference points of the measurements are Nasion (which is between nose and forehead), Inion (which is the lower point of the skull), vertex (which is the center point on the top of the skull), and pre-auricular points anterior to the ear. Moreover, F, T, O, and P denote the Frontal Lobe, Temporal Lobe, Occipital Lobe, and Parietal Lobe of the brain area. Sub-indexes indicate even or odd numbers for the right and left hemispheres [28].

Researchers are using three kinds of evoked potential to measure the electrical activity of the brain. Three kinds of evoked potentials are used to measure the human brain's neuron activity during a stimulus and response. They are:

Auditory Evoked Potential [29], Visual Evoked Potential [30], and Somatosensory Evoked Potential [31], respectively. In his 2017 study, Spüler wrote that Visual Evoked Potential (VEP) has significant communication speed in non-invasive EEG. To read an electrical signal from the brain gel-based electrode or dry electrode could be used. The application of gel-based electrodes takes more time to capture the signal. In order to create a more user-friendly BCI system, we can use dry EEG electrodes with a VEP-based system. However, it gives high variability between the subjects. Introduces averaging and dynamic stopping methods to mitigate the performance variability and deal with the lower signal-to-noise ratio of dry electrodes [32].

III. PREVIOUS WORKS IN EEG

Though the invasive method is sound in SNR and spatial resolution and apt to the BCI application, the risk factor is possible after the surgery [33]. Therefore, researchers are choosing the non-invasive method. The medical domain uses EEG for early identification of Alzheimer's, Parkinson, Paralyzing, and Epilepsy, and monitoring Anesthesia drug levels during surgery. Few researchers are also showing more interest in the non-medical domain, like decoding covert speech; this will be useful to impaired people, even brain-id for authentication purposes, Emotion detections, and in-home appliances.

The EEG signals have been used in many applications related to brain wave analysis, like the presence of epilepsy, to classify the covert word, brain-computer interface to activate external devices, and Emotion detection.

A. EEG Applications in Diagnosing Brain Disorders

1) Epilepsy: Conventionally neurologists go for a direct visual method to predict the epileptic abnormality. However, it takes more time to predict, may produce a variable result, and abnormality has limitations. Nowadays, to predict the above abnormality, a Computer-Aided Diagnosis is used [34]. In their work no separate steps for feature extraction and feature selection because they used the deep CNN model; this is one of the models in the deep learning technique [35]. The model will help predict Seizure disease. However, the data set was not enough for excellent performance, and the data should increase or apply data augmentation method [36] to achieve optimal performance of the result.

In another research, the author compared various Ensemble methods like bagging, boosting, Ada boosting, Multi boosting, random subspace, and rotation forest to discriminate the non-epileptogenic region of the brain with the epileptogenic location of the brain. They concluded that the rotation forest classifier had high performance [37].

2) Parkinson's disease: Many Parkinson's patients have a problem with locomotion. They will get stuck in forwarding movement while walking due to the Freezing of Gait (FOG) issue. One study revealed that it is possible to predict the FOG of Parkinson's disease (PD) before happening through EEG visual or auditory cues. The author investigated the specific EEG feature to implement real-time FOG prediction [38]. They used three layers-back propagation neural network model. They achieved 85.86% of sensitivity and a specificity of 80.25%.

B. EEG Applications in Emotions Detection

Emotions are the real feelings of humans, and the human brain controls them. Every human can have positive and negative emotions [39]. Positive emotions are love, happiness, surprise, joy, etc., as negative emotions are guilt, sadness, and annoyance. In various situations, they generate these emotions. If the emotions are within a limit, no problem for humans, or it may affect their health. Early identification of these problematic emotions makes it possible to reduce the many problems. Initially, the researchers detected these emotions using facial expressions, Text, or gestures [40]. They developed a model to recognize their facial expression or their gestures. However, nowadays, researchers are interested in using the human brain with the help of EEG. Much research has been available to classify emotions in the last decade. One study concluded that the neurons in the left hemisphere are active during positive emotions, and those in the right hemisphere are active during negative emotions [41].

C. EEG Application in BCI

One of the main aims of the BCI is to assist the paralyzed person in communicating with the outside world by controlling assistive devices through their brain signals without moving their legs or hands so that the dysfunctional motor system can bypass them. Some neuronal disorders cause patients to suffer significantly from impaired communication, including amyotrophic lateral sclerosis (ALS). As per the study by Chaudhary and his team in 2001, paralyzed patients could communicate with the aid of multiple brain-computer interfaces (BCI), including those that use electroencephalography [42].

P300 speller is one of the most popular BCI applications. There is a possibility to increase the performance of the P300 in practical usage. The author has examined the correlation between the P300 speller's versions with Rapid Serial Visual Presentation (RSVP) task features in this paper. In this study, the author identified the features of the correlation between the ERP (Event Relation Potential) and its behavior in offline binary classification accuracy. Using these features, the author proposed a simple multi-feature predictor. Their study revealed that a multi-feature predictor model could achieve higher predictability than the single-feature predictor model [43].

A recent study shows that a new system dimension controls the categories of people with speech problems and with ordinary people to assist them in everyday life by humming [44]. This article revealed the feasibility of EEG in BCI with vocal Imagery and vocal Intention. Four types of tasks were instructed to the subjects to perform, non-task specific (NTS), motor task (MT), vocal Imagery task (Vim), and vocal Intention task (VInt). The author concluded that the Vim task was highly classifiable in the EEG paradigm with BCI systems.

In their 2019 study, Kim et al. believe that the application of Brain-Computer Interface has been reaching out to non-medical applications too. That controls home appliances like a TV, digital door-lock, and electric light [45]. In another research, the author developed an assistive BCI system, which is helpful to differently-abled people. It will generate synthesized speech while the eye is blinking. During EEG recording, when the subjects notice the desired option on the display, they will wink their eyes; the system generates the synthesized speech per the options display. This system will be helpful to a patient who has a locomotive disorder like "locked-in syndrome"; this patient can communicate with their caretaker. This model could be used only for patients who have neurology disorders. Here the author suggested that instead of eyeblink EEG signals better to identify imagined movements through EEG signals [46].

D. EEG in Authentication

In information security, authentication is essential for in-person identification. Many techniques exist, like hand signature, password, fingerprint, iris, face, and voice recognition. However, all these have vulnerabilities. There is an alternative technique for every authentication technique, like forgery in the hand signature; the password can hack, film for fingerprint, contact lenses for the iris, face masks, and a voice vocoder [47]. Brain signature is the best solution because it is unique and cannot steal or hack. In one study, the author used only Alpha and Beta waves captured through EEG while subjects read 4-digit numbers when they saw numbers. A linear Discriminant algorithm (LDA) have used in the classifier. The training model has taken Common Spatial Analysis (CSA) values. Before authenticating, the trained model should have all the user's details. Finally trained model is used to authenticate the user [48]. In the later study, the author found that the delta wave has more specific information in user identification among all the five brain waves [47].

This research used biometric authentication to identify the individual using the brain signal system. The author captures EEG signals while performing three mental tasks with the participants. The author adapted a novel protocol and algorithm using NN and used mu and beta waves with a single trial analysis to test the novel algorithm. The Levenberg Marquardt back propagation algorithm trained NN. This research shows that the reading task is more suitable for biometric verification [49].

E. EEG in Imagined Speech

In the world, approximately nine billion people have problems speaking and hearing either by birth or accidentally last their speaking and hearing capability. It is tough for them to speak with ordinary people. With the same community, they can communicate with their sign language. (Communication between visually challenged and ordinary people is acceptable since they can speak well). Many researchers have developed an assistive tool that helps hard-of-hearing people communicate with ordinary people by converting sign language images into audible speech.

Recently researchers are showing interest in decoding the intended speech using brain waves invasively or non-invasively. In the last year, a few scientists have proven that imaged speech can interpret by implanting electrodes invasively using AI in the medical domain.

Imagined speech or covert speech, or inner speech, is a new paradigm used in the Brain-Computer interface to assist impaired people in communicating with the outside world for those who cannot produce the speech either partially or entirely or due to any health issues. Imagined or covert speech means thinking of a word without having articulation sound or tongue movement. An Imagined word could capture in EEG.

Since the last decade, researchers have been involved in imagined speech using EEG brain signals. Decoding silent speech will be helpful in many aspects like locked-in syndrome people, cognitive biometrics, and entertainment [50]. All the researchers used a complete band frequency with the different channels and subjects. However, Valuable information may not be present in the EEG signal during the analysis period <100ms. Better decoding accuracy in the classification, especially in the phase pattern in Theta and Delta waves [21].

This systematic review contains the classification performance result of the model. The researchers used the subjects to imagine the different vowels, consonants, words, both the vowel and words, and directions in symbols or words and objects. They used different classification algorithms. Most researchers applied benchmark algorithms like SVM, Random Forest, and LDA.

Methodologies used in imagined speech classification: Support Vector Machine (SVM) has been used in EEG classification for the diagnosis of neurological disorders [51]. This model was used effectively in many applications for disease prediction analysis, particularly in the medical domain. The linear SVM is an efficient technique for high-dimensional data application. Nowadays, researchers have used EEG brain signals to decode imagined speech. Support Vector Machine (SVM) is used in imagined speech analysis using EEG signals. The following article has evidence of the application of SVM to classify vowels and consonants [21, 52, 53]. To classify the Imagined word [50]. In one more repeated study, SVM as a benchmark algorithm is used to classify the vowels [54].

Extreme Learning Machine (ELM) is another effective classifier. Many real-time applications use the ELM technique. It is for binary as well as multi-class classification. It has a high learning speed, so researchers have used this model in robotic applications [55]. Since its fast-learning capability and no iteration, the reason is that a single hidden layer connects the output layer; it is used in EEG applications to classify the imagined vowels and words [53, 56]. The performance of ELM in sparse high-dimensional applications which are currently under investigation [57].

In Decision Tree (DT), only training data is sufficient because once the decision tree is present with the help of training data, it can support new samples. While classification, new data was inserted without disturbing the entire tree. Moreover, it is very flexible to include the sample [58].

The importance of channel selections and reducing electrodes are in the next section. For these, the decision tree algorithm is suitable because EEG signals may contaminate with noises or contain irrelevant information, which will reduce the classification's performance. One study revealed that a decision tree could improve performance.

Furthermore, the authors proved that the decision tree is better than the following algorithms: Mutual information, SVM, CSP coefficient, and Fisher's criterion, respectively [59]. It is easy to interpret the brain signal by a decision tree. However, if the data set is large, then it is challenging. For smaller data decision tree is more suitable for decoding silent speech [50, 60].

Random Forest (RF) is another classifier. Recent study proved that sufficient electrodes could reduce the time and effort in analysis during EEG signal classification by the time Random Forest model [61]. The random forest model is an improved version of the decision tree, widely used in EEG signals classification. The Random Forest model is used as a benchmark classifier to classify vowels and words [54] and in the imagined word classification[50].

Linear discriminant analysis (LDA) is a familiar feature reduction technique to project the features in higher dimension space into lower dimension space. Moreover, as a classifier, it is used. It creates a new axis from the features, reducing the variance and increasing the two variables' class distance. The main drawback of LDA in feature reduction is required all the features as the input signal. The new feature is calculated based on all the observations. This situation will not occur in real-time BCI applications [62].

K-Nearest Neighbor (KNN) is a multi-class classifier. It does not take training duration; the reason is that the data itself is a model. Implementation is straightforward when compared with another classification algorithm. The reason is that it just calculates the distance between the different features using either Euclidian or Manhattan**.** Moreover, it has only one hyper-parameter k and several clusters. However, it has a few drawbacks also.

For small datasets, it works well, but not in large datasets and high dimensional data sets. It also takes more cost to calculate the distance. Noise and missing data can affect this model. In the imagined word classification, Naïve Bayesian and MLP models are used [50, 63].

Classifying the EEG signal with a few layers in CNN is impossible. For better classification accuracy Deep Neural Network could be the best for the EEG imagined data [64]. CNN[54, 64, 65] RNN and DBN[66], DNN[67]. The DBN was introduced in 2006 and, in the next year, was analyzed by Bengio [68]. The table shows the pros and cons of the various classifier.

1) Subject focused on imagine vowel and consonant: Table II depicts various studies involved in classifying imagined speech with vowel and consonant using different model. One study shows the discrimination between the vowel sound of /a/, /u/, and rest as control states for the imagined. The vowel /a/ and /u/ was the following muscles involved while uttering these vowels. They are digastric and Orbicularis Oris muscles [52]. They used a linear classifier and SVM to give the excellent performance result in the table.

TABLE II. IMAGINE VOWELS AND CONSONANTS

Reference	Vowels/ Consonant	Classifier	Performance
[21]	/a/, /e/, /i/, /o/, /t/	SVM	δ, θ has better classification accuracy in the phase pattern
[52]	/a/, /u/, rest	Linear, SVM	87.5 – 100% 78.33 – 96.67
[53]	/a/,/e/,/i/, /o/, /u/	ELM	68.5%
[65]	/a/,/e/,/i/, /o/, /u	CNNeeg1-1 Compared with DL Shallow CNN	65.62% in BD1 and 85.66% in BD2

In another study, the vowels /a/, /u/, / i/, /o/, and /u/ were used. They aimed to classify the imagined speech of EEG using a single trial [53].

In the Feed-Forwarded Neural Network [6], all the weights and biases are necessary to tune each layer. It slows down the process. Therefore, the author used the ELM method. G. Huang invented ELM [53, 57], which uses random weight to calculate output weight analytically. Hence learning speed is significantly high compared with other conventional neural network algorithms.

Normally classifying EEG data gives poor generalization overfitting due to limited samples. However, the generalization was good in this research and achieved minimum squared training error. The result shows that the ELM and its variants have better classification results than other algorithms [53].

One more research conducted used all the vowels /a/, /u/, /i/, /o/, /u/ and created a new dataset with 50 subjects. In this, they proposed a new algorithm named CNNeeg1-1 in deep learning to classify imagined vowels in EEG signals and compared the performance of CNNeeg1-1 with DL Shallow CNN and EEGNet benchmark algorithm by an open-access dataset (BD1) and a new dataset (BD2). CNNeeg1-1 performs better than the other mentioned algorithm, with 65.62% in BD1 and 85.66% in BD2 [65].

Another study used English alphabets /a/, /e/, /i/, /and /t/ they identified that the EEG phase signals have more information than the other frequency band of the EEG signal during auditory and visual stimuli. So decoding accuracy is more in EEG phase signals than the power information.

Also, it is possible to get good accuracy in decoding during the time between 180ms and 300ms after the appearance of the stimulus [21].

Subject focused on imagine words: Table III shows that some of the researchers used specific words instead of using either vowels or consonants. So that the model will be helpful to persons who are not able to speak or not able to move their bodies; they could get help from the caretaker.

TABLE III. IMAGINED WORDS

Reference	Words	Classifier	Performance
[10]	Go, back, left, right, stop	ELM	40.30% and 87.90% in multi-class and binary class
[50]	Sos, medicine, stop	RF, DT, KNN, SVM	76.4% in theta wave.
[63]	Yes, no, the rest state	MLP	Yes vs. rest 73.73% No vs. rest 75.38% Ternary classification 53.91%
[66]	10 CVC	RNN, DBN	72% & 80%
[67]	In, Cooperate	DNN	71.8 %
[69]	Forward, backward, up, down, help, take, stop, release	ResNet18+2GRU	85%
[70	Ambulance, hello, light, stop, toilet, water, clock, help me, pain, thank you, TV, and Yes.	RF, SVM	39.73±5.64% in imagined speech. 40.14±4.17% in visual imagery.

It is possible to develop more intuitive BCIs for communication-based on BCI activation tasks involving covert speech. The author used 'Yes' and 'no' as imagined words [63]. In the same year, Quresh et al. conducted more research to classify the five words: go, back, left, right, and stop. They used a sigmoid activation function-based linear ELM classifier and all the frequency bands. The author suggested that δ and α can be used instead of all the frequencies. Because more activation processes were present in that frequency band [10], they achieved good classification results in both the multi-class and binary classification.

In another research, the author suggested that acquiring EEG signals from more channels will increase the training data size. It improves the classification accuracy in the deep learning technique [67]. Furthermore, channel selection also has a vital role [18]. It is easier to train a DNN if the selected channels correspond to individual imagined words and are considered independent data vectors [67]. This author has taken two words to decode one short word, 'in' and one long word, Cooperate, and the DNN model gave a 71.8% performance result. A large data set is required to build a neural network classifier for good accuracy. In another paper, Vorontsova confirmed that a small data set is enough to construct a more accurate neural network classifier on EEG in a single participant subject rather than a group of subjects with an extensive data set. In addition, they concluded that limited sample EEG data could apply to the general population [69]. In silent EEG, speech recognition with Russian words: Forward, backward, up, down, help, take, stop, release, and pseudo-word. The research conduct result shows that RNN yields good accuracy than CNN.

To identify the vowel from Consonant-Vowel-Consonant words were used RNN and DBN models. From the brain connectivity estimator result, the author identified that more electrons are activated during speech and imagery speech in the left frontal and left temporal portions. Deep Belief Network has given a better classification result than the RNN [66].

A recent study by Agarwal & Kumar (2021) analyzed all the brain waves of the three words of silent speech sos, medicine, and stop. The research result was 76.4% accuracy in the theta wave. This research identified that more details would be available in theta and high gamma waves during a silent speech [50]. Moreover, some words share a similar pattern in brain activity [69]. Decoding EEG signals with more classes is also not advisable. In multi-class classification, the author found that the decoding performance may reduce moderately due to the more feature in imagined and visual imagery speech while decoding imagined words [70].

TABLE IV. IMAGINE VOWELS AND WORDS

Reference	Vowels/Words	Classifier	Performance
[54]	/a/, /e/, /i/, /o/, /u/ up, down, left, right, backward, forward	CNN	Word accuracy 24.97% Vowel accuracy 30%
[64]	/a/, /e/, /i/, /o/, /u/ up, down, left, right, backward, forward	CNN, TL	CNN-23.98% and 24.77%, 24.12%, 23.22%

2) Subject focused on imagine vowels and words-repeated study: Table IV depicts two research conducts have done the repeated study with the same open-access data set created by Coretto but used a different method to classify the word [54, 64]. The article's main objective was to enhance the classification result by decoding imagined speech in EEG using DL with Hyper-parameter optimization [54,71] on classifier performance. They tried both overt and covert speech. From this, the author concluded that CNN has significantly better accuracy than SVM, RF, and rLDA classifiers. All the classifiers used the nCV method for HP optimization. The result shows that the robust selection of HP in CNN for decoding was critical. The effect of the model determines by the number of epochs, activation function, and learning rate. So, the selection of optimal HP depends on the other hyper-parameters [54]. The author proposed a new CNN for the classification in the subsequent repetition study. The idea was to reduce the complexity, retaining the same accuracy, but the result has shown considerably less accuracy. The author recommended more data and powerful machine learning algorithms to increase accuracy. The effectiveness of the neural network improved through transfer learning [72].

The research revealed that the brain signal is unique for the same imagined action in a different subject [64]. Subject focused on imagine directions: Feature extraction and classification have a vital role in any BCI system. Researchers have used classical approaches like pattern recognition in feature extraction and classification for decades. Now many researchers are applying a deep learning approach in many areas. Few researchers have introduced the deep learning method into the study of biomedical signals, especially EEG signals. Table V shows that the subjects were imagined the directions instead of vowel, consonant, or words.

TABLE V. IMAGINE DIRECTIONS

Reference	Direction	Classifier	Performance
[56]	Left, right, up, and down	ELM multi & binary	49.77%
[73]	+, ← or → Both feet and tongue	CNN	92.7%

In their research, input has been taken based on wavelet transform; the time-frequency input images acquired in the C4, C3, and Cz channels; resize technique is applied to the input image to minimize the training duration in 2D CNN. The research result shows that the proposed method is more efficient in the 1D kernel with fewer parameters. However, it has challenges in performance due to the quality of the signals and limited samples [73]. Another research proposed by Pawar & Dhage (2020) in multi-class covert speech classification using an extreme learning machine (ELM). The ELM provides the generalized and optimal solution in multi-class covert speech recognition. It has the advantage of training and testing the model will take less cost because it is a single hidden layer feed-forward neural network. It is not required to tune the weights. Moreover, the author has shown that the EEG signals taken from a particular region in the brain will be sufficient instead of acquiring signals from the entire brain. Their future challenge is to develop an intelligent algorithm to classify many words in real-time [56]. The authors have taken three different brain areas; Brain Area 1 was the Prefrontal cortex, right inferior frontal gyrus, and Wernicke's and Broca's areas. Brain Area 2 is the same as Brain Area 1, and Brain Area 3 is the entire brain area.

3) Subject focused on imagined object: Table VI shows that the objects were used instead of imagine vowel, consonant and word.

TABLE VI. IMAGINED OBJECT

Reference	Objects	Classifier	Performance
[60]	Cube, Rectangular prism, Pyramid	Decision tree	43%

The author used two visually challenged subjects and two sighted subjects to recognize the objects. The author achieved 43% classification accuracy, which was less. Still, it could be 90% accurate for an enormous decision tree, but if it is too large, it is not easy to analyze. The author revealed that sighted people could identify the object through their vision signal though blindfolded. It means the occipital lobe was significantly active. However, visually impaired people identified the same things by sensing only. Neurons in the parietal lobe were active [60].

However, this decoding of covert speech is in the NP-Hard problem only; we hope it will soon be NP-Complete. If researchers achieved 100% success in decoding covert speech and deploying it successfully, many impaired people could lead better life in society.

IV. SIGNIFICANCE OF THE NUMBER OF CHANNELS AND SUBJECTS, KEY CHALLENGES

It is essential to select the proper electrodes and their locations. If fewer electrodes are selected correctly, they may retain critical information. If too many electrodes are selected, then it may produce redundant information. Similarly, the number of subjects is essential to acquire the EEG signals for better classification results. Training a model with significantly fewer data will be an issue with underfitting. Sometimes an over-fit problem may occur after training a model with sufficient data. So, it is necessary to have more subjects and attention to place sufficient electrodes in the scalp location as per the researchers' application. In one research, the authors stated that increasing the number of electrodes in the front temporal of the brain's left hemisphere could improve the imagined speech signal reorganization [65].

Many researchers showed more interest in decoding imagined speech using the non-invasive method. Various techniques were used to increase the accuracy of the classifications; however, it is hard to implement in a real-world scenario. Because of an insufficient EEG data set, takes long calibration time, Poor SNR and non-static signal. These are all significant challenges to the researchers.

V. CONCLUSION

In this systematic review, number of studies reviewed, which reveals a promising result for decoding imagined speech using vowels, consonants, words, directions and objects from EEG signals. However more work required to be conducted to interface with the machine and human. And also, we have observed that very few imagined data sets are available for BCI applications but still need to be adequately deployed in BCI applications due to a lack of data. Furthermore, all the available EEG data sets pertain to normal and healthy subjects only, particularly in decoding imagined speech. Any BCI model developed using the available data set will be helpful to people who have brain disorders while they are growing up or who are injured accidentally or due to illness. But may not be helpful to disabled people by birth itself.

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Edge Detail Preservation Technique for Enhancing Speckle Reduction Filtering Performance in Medical Ultrasound Imaging

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***Abstract*—Ultrasound imaging is a unique medical imaging modality due to its clinical versatility, manageable biological effects, and low cost. However, a significant limitation of ultrasound imaging is the noisy appearance of its images due to speckle noise, which reduces image quality and hence makes diagnosis more challenging. Consequently, this problem received interest from many research groups and many methods have been proposed for speckle suppression using various filtering techniques. The common problem with such methods is that they tend to distort the edge detail content within the image and blurring is commonly encountered. In this work, we propose a new method that could be combined with previous speckle suppression techniques to preserve edge detail content of the image. The original image is first processed to extract the edge detail content. Rather than presenting the original method to the speckle suppression filtering technique, the edge detail content is subtracted from the original image before it is filtered. Then, such edge detail content is added to the output of filtering to form the final image. The new method is practically verified using 26 imaging experiments as well as ultrasound images from publicly available databases in combination with four widely used speckle reduction filters. The results are evaluated qualitatively and quantitatively using standard image quality metrics.**

***Keywords*—Edge detail preservation; image quality metrics; speckle reduction; ultrasound imaging**

I. Introduction

Ultrasound imaging stands out as a widely embraced clinical imaging technique, lauded for its safety, cost-effectiveness, and diverse soft tissue imaging applications encompassing abdominal imaging, echocardiography, and obstetrics and gynecology [1]. The mechanism involves emitting low-intensity acoustic wave pulses into the body, capturing the reflected and scattered echoes from internal structures to construct a cross-sectional anatomical image. With its inherent safety and an impeccable track record in clinical applications, ultrasound imaging stakes its claim as the safest imaging modality to date. Its prevalence in critical applications, such as monitoring fetal growth and assessing biophysical profiles during pregnancy, attests to its reliability. The technology spans a spectrum, ranging from basic handheld units costing a few thousand dollars to sophisticated systems tailored for specialized applications like echocardiography, commanding prices in the hundreds of thousands. This versatility ensures accessibility in rural and low-income communities and integration into large, specialized hospitals, poised to become as indispensable to medical practice as the stethoscope.

Despite the myriad advantages of ultrasound imaging, a glaring issue persists in the quality of its images compared to other modalities. The visual noise and the requisite training to correlate anatomy with ultrasound images stem from speckle, a persistent problem since the inception of ultrasound imaging. Research efforts, both academic and industrial, have focused on mitigating speckle noise in ultrasound images due to its undeniable impact on the technology [2].

Speckle noise emerges inevitably as a direct consequence of the underlying physics in ultrasound imaging. The process involves transmitting an ultrasonic pulse through the body using a 1D or 2D array-formatted ultrasonic transducer. This pulse propagates through tissues, engaging with their various components, resulting in reflected waves from specular reflectors and scattering from point reflectors [1]. The distinguishing factor between specular and point reflectors lies mainly in size; specular reflectors surpass the ultrasound wavelength, while scatterers are notably smaller than this wavelength, typically a fraction of a millimeter within the 2-15 MHz range of ultrasound imaging frequencies. Consequently, tissue interfaces and major blood vessels mimic specular reflectors, while blood capillaries and cells within the extracellular space act as scatterers [3][4]. In tissues like the liver, hepatocytes independently scatter ultrasound waves, with the backscattered part received by the ultrasound transducer. Given the dependence on ultrasound transducer frequency, orientation, and the intricate 3D tissue structure, the received scattered waves from myriad cells interfere, creating a pattern of partial constructive and destructive interference points that manifest as random noise in the image. The crucial disparity between speckle noise and true random noise lies in the former's persistence under unaltered imaging conditions, resisting improvement through averaging or conventional methods [5][6].

Numerous approaches have been proposed to tackle the challenge of speckle reduction, broadly categorized as either acquisition or post-processing methods. Acquisition methods aim to diminish speckle by acquiring multiple versions of the same slice with varying beamforming parameters, such as steering, focal point, and frequency [7] [8]. Although this approach appears straightforward, its practical implementation demands the reprogramming of acquisition protocols for different applications, incurring substantial costs and posing challenges in applications requiring high frame rates or specific acquisition sequences, such as in 3D and 4D imaging [8]. Alternatively, the second approach, centered on postprocessing, has garnered attention from research groups since the 1980s. The fundamental premise involves commencing with the acquired image and applying diverse filtering strategies to suppress speckle noise. This approach mandates only a digital processing platform and access to the ultrasound imaging system's frame buffer. It can also operate on an external computer with a frame grabber or other means to collect ultrasound images without altering the existing system. Given the advancements in modern computing platforms, including parallel processing and GPUs, this approach emerges as the pragmatic starting point for practical purposes with existing ultrasound imaging systems. Technically, most classical post-processing methods fall into four main categories, with hybrids across them—linear, nonlinear, diffusion-based, and wavelet-based filtering methods [2]. Linear filters encompass techniques like first-order statistics filtering, local statistics filtering with higher moments, and homogeneous mask area filtering [9], [10], [11]. Nonlinear filtering methods include median filtering, linear scaling filter, geometric filtering, and homomorphic filtering [12], [13], [14], [15]. Diffusion-based methods include various variants of anisotropic diffusion filtering [16], [17], [18], [19], [20]. Wavelet-based methods primarily operate using wavelet shrinkage with different wavelet families and levels of composition [21], [22], [23], [24]. Hybrids incorporating elements from these methods have also been introduced [25], [26], [34], [35]. Other approaches include methods that use a human visual system model to reduce the appearance of noise in ultrasound images [36], and methods involving deep learning using convolutional neural networks to build despeckling models from training custom-designed networks [37], [38].

Despite the strides made in speckle reduction methods, challenges persist in bridging the gap between the perceived quality of processed images by researchers and clinicians. The apparent smoothness achieved by these methods may compromise crucial edge details, significant to clinical sonographers. To harness the full potential of existing techniques, there is an imperative to enhance their performance and align them more accurately with the clinical perspective on image quality [27]. Recognizing the substantial contributions of current techniques is vital, but addressing their common shortcomings is crucial to maximizing their efficacy in routine clinical ultrasound applications.

In this work, we propose a new method that could be combined with previous speckle suppression techniques to preserve edge detail content of the image. The original image is first processed to extract the edge detail content. Rather than presenting the original method to the speckle suppression filtering technique, the edge detail content is subtracted from the original image before it is filtered. Then, such edge detail content is added to the output of filtering to form the final image. The new method is experimentally verified using 26 imaging experiments as well as ultrasound images from publicly available databases with four widely used speckle reduction filters. The results are evaluated qualitatively and quantitatively using image quality metrics.

II. Methodology

Ultrasound image acquisition involves gathering a series of lines (or sticks) extending across the scanned area, arranged either linearly or in a sector pattern, contingent upon the employed imaging probe. The acquired data, referred to as stick data, serves as the foundation for generating a properly formatted output image through image reconstruction techniques, leveraging the provided geometry information. The new method starts from estimating the edge detail content from the original stick data. It works by applying edge detection techniques such as Canny edge detection to the original stick data to generate a map of the locations of salient edge detail features [27]. To better include the complete edge detail features and take into account having a smooth transition to their surroundings in the subsequent steps, the generated edge map is blurred using a simple spatial domain filtering with a Gaussian kernel. The normalized version of the outcome is used as a mask that is multiplied by the original stick data to extract the edge detail content. A version of the original stick data that contains only the edge detail-free parts of the data is computed by subtracting such edge detail content from the original stick data. The detail-free data is used as the input to the speckle reduction filtering method. The restoration of edge detail content to the filtering output is done by adding them. The basic block diagram of the new edge detail preservation method is shown in Fig. 1. In order to visually illustrate the steps of the process, example stick data for all steps of the process are presented in Fig. 2 with comparison to the stick data output from the original speckle filtering alone.

The implementation and testing of the novel edge detail preservation method involved four widely adopted speckle reduction filtering techniques, serving as representative examples from each of the four primary post-processing categories, without sacrificing generality. These techniques were wavelet denoising [21], [23], relaxed median (RMedian) denoising [14], [15], speckle reducing anisotropic diffusion (SRAD) [17], [16], [18], and local statistics based filtering (Lee) [9], [10]. In each of these techniques, the original technique is implemented with the implementation details suggested in the most recent variant. In order to quantitatively assess the image quality improvement, eleven image quality metrics are compared between the original filtering technique alone and its combination with the new edge detail preservation method. The image quality metrics used are geometric absolute error (GAE) [2], mean-squared error (MSE) [2], Laplacian mean-squared error (LMSE) [28], normalized absolute error (NAE) [28], Minkowski error metric (for β=1, 3, 4) [29], universal quality index (Q) [30], structural similarity index (SSIN) [29], signal-to-noise ratio (SNR) [31], and peak signal-to-noise ratio (PSNR) [31].

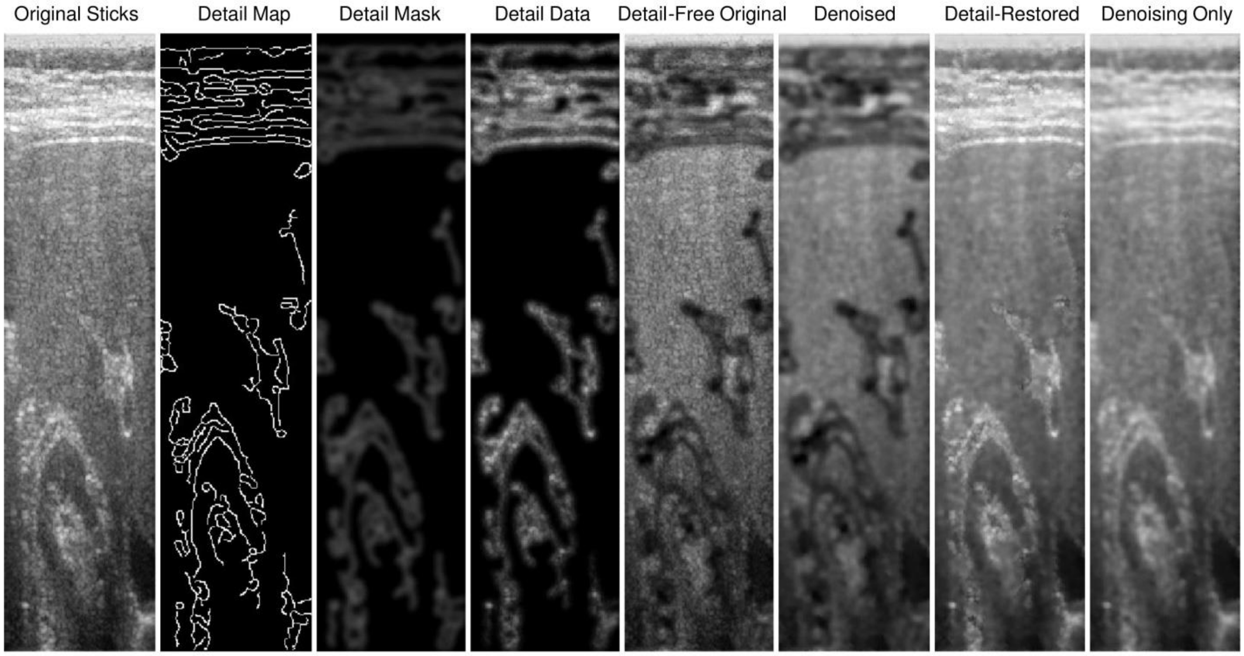

Fig. 1. Illustration of outputs at each block of the proposed edge detail preservation method. The last image to the right illustrates the output of the speckle suppression filter without the new method for comparison.

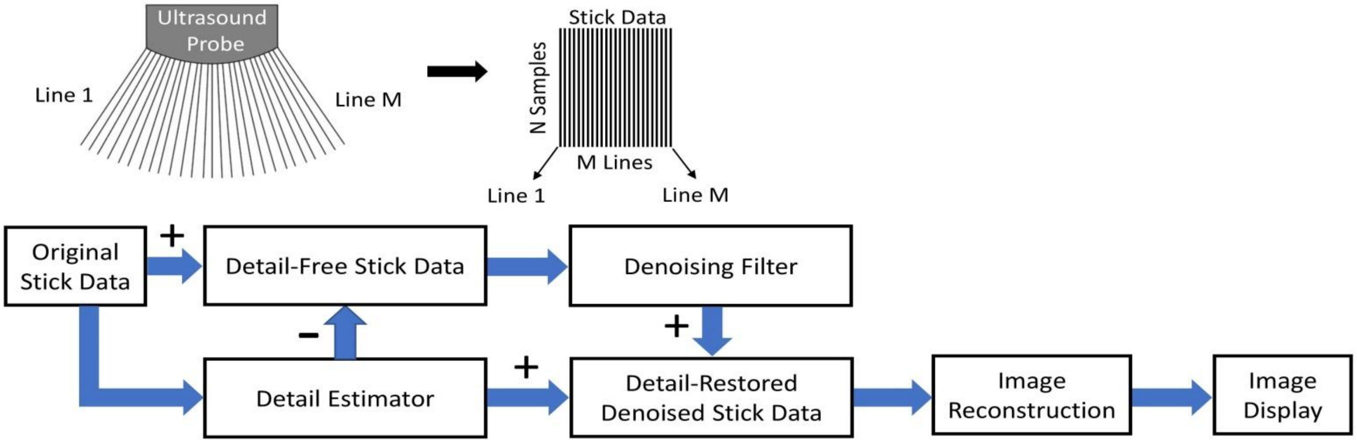

Fig. 2. Block diagram of the proposed edge detail preservation method applied to experimental stick data. The same block diagram applies to images from public databases without need for image reconstruction block.

III. Experimental Verification

The proposed method was verified using collected experimental ultrasound imaging data as well as ultrasound imaging data from publicly available resources. While the latter come in the form of image files encoded using 8-bit image formats such as Joint Photographic Experts Group (JPEG) or Portable Network Graphics (PNG) formats, the collected experimental data come in the form of raw data at a higher quantization rate of 16 bits.

The acquisition of ultrasound imaging data employed the Digison Digital Ultrasound Research system from Mashreq, Egypt. This system, featuring a customized research interface, facilitated image acquisition control with the capability to access and store raw radiofrequency sampled data for each image line. To ensure a representative spectrum of applications, ultrasound array probes, including convex array abdominal probes, small parts linear probes, and tight convex array endo-cavity probes, were utilized. Imaging experiments spanned various clinical applications, conducted on human volunteers and a quality control tissue-mimicking phantom (Multi-Tissue Ultrasound Phantom CIRS Model 040GSE, CIRS Inc., U.S.A.). Each imaging experiment focused on a specific region, employing a designated imaging probe, and entailed collecting 10 images for each application to derive an average, minimizing interference from random noise in speckle reduction filtering. The total number of conducted imaging experiments was 26, yielding a total of 260 images. Fig. 3 illustrates the diversity of images from these 26 experiments. The research interface facilitated raw image data collection at a sampling rate of 50 M samples/s with 16 bits of quantization. Signal processing involved filter-based Hilbert transformation for peak detection, followed by resampling to yield 512 data samples per line (or stick). The resultant stick data formed a 512×128 array that could subsequently use to reconstruct the final image using scan conversion and interpolation.

The ultrasound imaging data from publicly available resources were obtained from the Breast Ultrasound Imaging (BUSI) database [32] and the B-mode ultrasound imaging cases from Ultrasound Cases training web site [33]. The BUSI database comprises breast sonography images collected from women aged 25 to 75 years in 2018. The dataset encompasses 600 female patients, containing a total of 780 images with an average size of 500 by 500 pixels, provided in PNG format. On the other hand, the data from Ultrasound Cases website are put together through a collaboration between SonoSkills (a provider of ultrasound training in Europe) and FUJIFILM Healthcare Europe. (a manufacturer of medical imaging products, encompassing ultrasound, MRI, and X-ray). The database comprises information gathered from 7678 cases, covering a diverse range of applications, including liver, urinary tract, male reproductive system, gynecology, breast and axilla, as well as musculoskeletal joints and tendons. From this database, a total of 2428 images of size 225 by 300, specifically representing B-mode images, were utilized. Therefore, the total number of images from combining both databases is 3208 images.

The stick data (experimental data) or image (public database data) underwent detection of edge detail mapping using Canny edge detection with thresholds of 0.1 and 0.4 for strong and weak edges, respectively, in both vertical and horizontal directions [27]. Subsequently, a 2D Gaussian spatial filter with a kernel size of three created a mask, which was then multiplied by the original stick data to extract the edge detail content. This content served two purposes: first, subtracted from the original stick data to form detail-free stick data, serving as input for speckle reduction filtering; second, restored to the filtering output to create the final image. The processing steps for experimental stick data are visualized in Fig. 1, with illustrations of the data at each step in Fig. 2. It should be noted that the same diagram applied to public database data with no need for the image reconstruction step. The image quality assessment involved eleven quantitative metrics, comparing output from the speckle suppression filter with and without the edge detail preservation technique. Averaging metrics from the 26 experiments provided reliable comparisons, and standard deviations were computed. Percentage improvement facilitated observation of relative changes across metrics with different numerical ranges. The statistical significance between the two sets of results across experiments was evaluated using the p-value of a two-sample t-test to test the null hypothesis that the observed differences in image quality metrics come from the same distribution where such hypothesis is rejected at a significance level of 0.05.

The final image reconstruction utilized scan conversion and/or interpolation, aligning with array geometry and dimensions to present the image in the correct spatial format. All processing occurred on Matlab 2023a (Mathworks, Inc.) with an educational license from King Abdulaziz University. The computing platform featured an HP Omen 25L personal computer with an 11th generation Intel® Core™ i7-11700F running at 2.50 GHz, using a 64-bit Windows 11 Home Edition, and equipped with 32 GB of RAM.

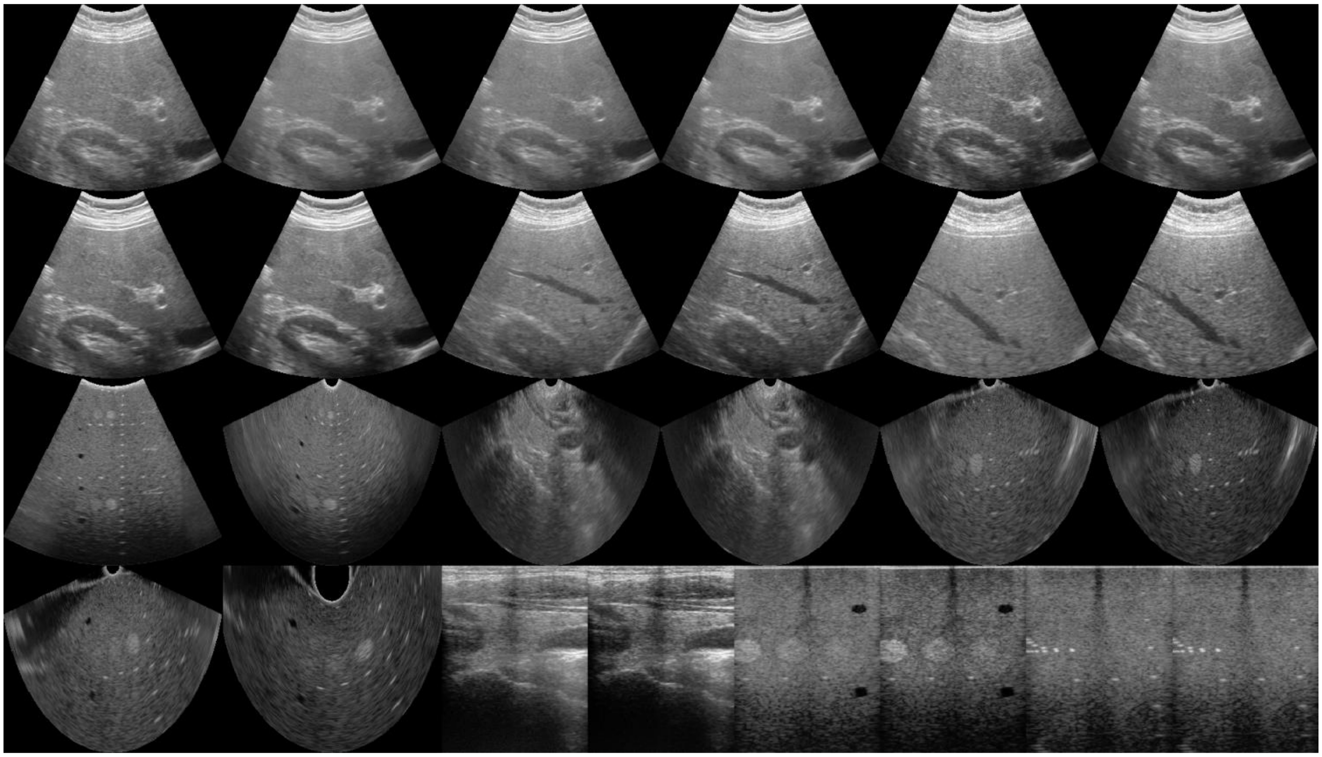

Fig. 3. Visualization of diverse imaging experiments conducted in this investigation.

IV. Results and Discussion

For the experimental data, Fig. 4 presents the output image results stemming from the implementation of the novel edge detail preservation technique, coupled with four illustrative techniques representing the prevailing approaches in speckle reduction for sample applications. Also, Fig. 5 presents magnified versions of parts of the output image results in Fig. 4 to better demonstrate the effect of the new edge preservation method. The considered previous techniques encompass the widely used methods of wavelet denoising [21], [23], relaxed median (RMedian) denoising [14], [15], speckle-reducing anisotropic diffusion (SRAD) [17], [16], [18], and local statistics-based filtering (Lee) [9], [10]. The original images are provided in the left column with the outputs of the four techniques on the first row and their combination with edge detail preservation technique on the second row in each application. As can be observed, the details are sharper with the new method for all techniques and across different applications.

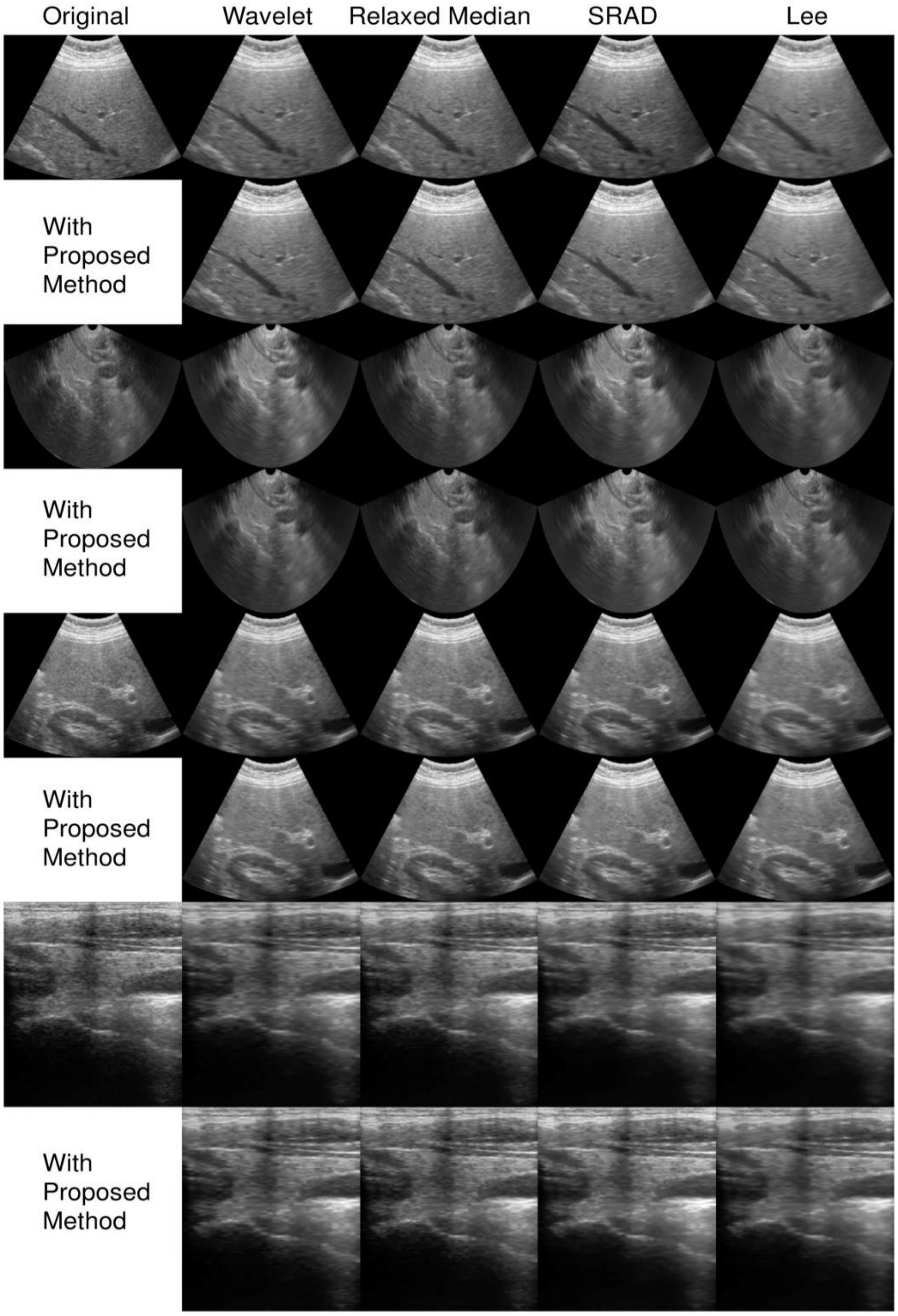

Fig. 4. Diagram showing the output image results from the original speckle suppression techniques (first row of each experiment) and combined with new edge detail preservation method (second row of each experiment) for four example experiments with original image in the left column.

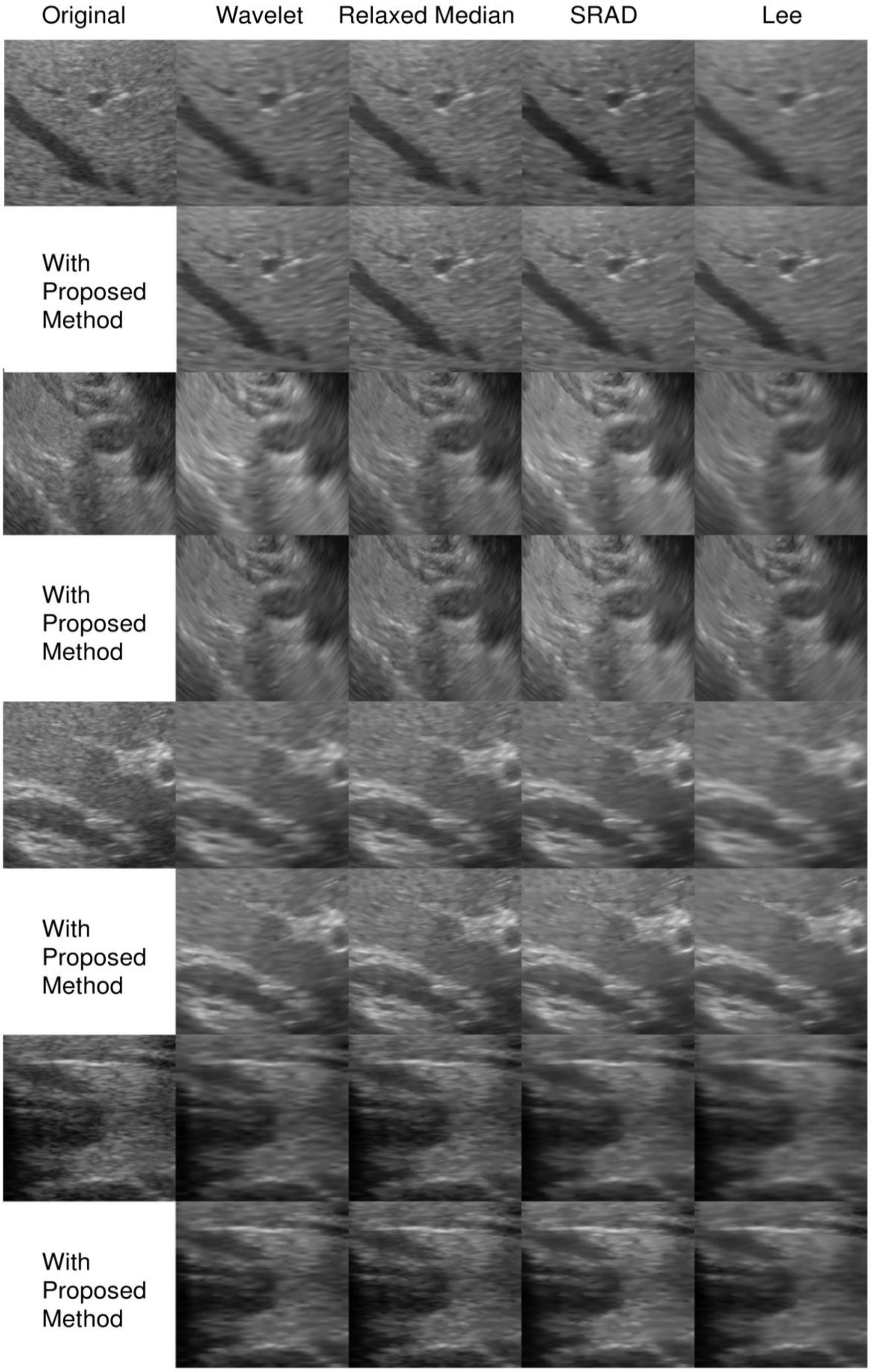

Fig. 5. Magnified parts of the output image of Fig. 4 showing results from the original speckle suppression techniques (first row of each experiment) and combined with new edge detail preservation method (second row of each experiment) for four example experiments with original image in the left column.

TABLE I. IMAGE QUALITY METRICS BEFORE AND AFTER APPLICATION OF PROPOSED EDGE PRESERVATION TO ORIGINAL SPECKLE REDUCTION METHOD, AND ITS STANDARD DEVIATION CALCULATED ACROSS THE SET OF 26 EXPERIMENTS

Quality Metric	Wavelet		Relaxed Median		SRAD		Lee	
	Before	After	Before	After	Before	After	Before	After
Geometric Average Error (GAE)	**3.51** ± 0.61	**2.96** ± 0.49	**2.06** ± 0.35	**1.70** ± 0.29	**4.83** ± 2.28	**3.93** ± 1.56	**3.57** ± 0.57	**2.88** ± 0.47
Mean Squared Error (MSE)	**114.89** ± 31.32	**59.94** ± 19.30	**71.58** ± 16.25	**30.23** ± 9.06	**184.80** ± 156.31	**94.87** ± 63.92	**120.8** ± 30.24	**57.81** ± 18.37
Laplacian Mean Squared Error (LMSE)	**0.99** ± 0.04	**0.67** ± 0.08	**0.94** ± 0.07	**0.66** ± 0.08	**0.62** ± 0.13	**0.41** ± 0.1	**0.95** ± 0.13	**0.61** ± 0.08
Normalized Absolute Error (NAE)	**0.07** ± 0.01	**0.05** ± 0.01	**0.04** ± 0.01	**0.03** ± 0.01	**0.09** ± 0.05	**0.07** ± 0.04	**0.07** ± 0.01	**0.05** ± 0.01
Minkowski Error Metric (β=1)	**7.53** ± 1.22	**5.89** ± 0.97	**4.47** ± 0.67	**3.40** ± 0.57	**10.19** ± 4.82	**7.65** ± 2.93	**7.47** ± 1.14	**5.74** ± 0.94
Minkowski Error Metric (β=3)	**15.82** ± 2.25	**9.24** ± 1.51	**15.08** ± 2.19	**8.55** ± 0.84	**17.00** ± 4.41	**10.71** ± 3.09	**16.11** ± 2.29	**9.15** ± 1.45
Minkowski Error Metric (β=4)	**22.8** ± 4.11	**10.77** ± 1.75	**23.52** ± 3.66	**14.89** ± 1.24	**23.35** ± 4.72	**11.98** ± 3.18	**22.99** ± 4.08	**10.73** ± 1.66
Universal Quality Index (Q)	**0.57** ± 0.04	**0.64** ± 0.04	**0.80** ± 0.04	**0.84** ± 0.04	**0.74** ± 0.08	**0.78** ± 0.08	**0.57** ± 0.05	**0.65** ± 0.05
Structural Similarity Index (SSIN)	**0.66** ± 0.06	**0.72** ± 0.06	**0.84** ± 0.04	**0.87** ± 0.04	**0.81** ± 0.04	**0.85** ± 0.04	**0.66** ± 0.05	**0.74** ± 0.05
Signal-to-Noise Ratio (SNR)	**23.97** ± 1.27	**26.88** ± 1.78	**25.99** ± 1.16	**29.84** ± 2.08	**22.78** ± 3.10	**25.71** ± 3.3	**23.72** ± 1.03	**27.02** ± 1.72
Peak Signal-to-Noise Ratio (PSNR)	**27.65** ± 0.97	**30.41** ± 1.34	**29.27** ± 0.83	**33.25** ± 1.52	**26.40** ± 2.93	**29.39** ± 2.64	**26.83** ± 0.78	**30.48** ± 1.27

TABLE II. AVERAGE PERCENTAGE ALTERATION IN IMAGE QUALITY METRICS FOLLOWING APPLICATION OF PROPOSED EDGE PRESERVATION TO ORIGINAL SPECKLE REDUCTION METHOD AND PERCENTAGE STANDARD DEVIATION ACROSS THE SET OF 26 EXPERIMENTS

Quality Metric	Wavelet	Relaxed Median	SRAD	Lee
Geometric Average Error (GAE)	**-15.65%** ± 5.42	**-17.47%** ± 5.08	**-18.66%** ± 6.49	**-19.31%** ± 4.37
Mean Squared Error (MSE)	**-47.83%** ± 14.48	**-57.77%** ± 18.59	**-48.66%** ± 13.97	**-52.14%** ± 14.63
Laplacian Mean Squared Error (LMSE)	**-32.48%** ± 9.28	**-29.83%** ± 9.61	**-33.08%** ± 9.50	**-36.13%** ± 13.91
Normalized Absolute Error (NAE)	**-19.98%** ± 6.65	**-23.88%** ± 6.94	**-22.52%** ± 9.75	**-23.16%** ± 5.77
Minkowski Error Metric (β=1)	**-19.81%** ± 5.16	**-23.89%** ± 4.81	**-24.94%** ± 7.85	**-23.11%** ± 4.43
Minkowski Error Metric (β=3)	**-41.56%** ± 14.14	**-43.29%** ± 15.34	**-36.98%** ± 18.41	**-43.22%** ± 14.27
Minkowski Error Metric (β=4)	**-52.75%** ± 19.45	**-36.72%** ± 12.99	**-48.7%** ± 24.3	**-53.34%** ± 19.0
Universal Quality Index (Q)	**+11.35%** ± 4.17	**+4.26%** ± 1.62	**+4.88%** ± 2.01	**+14.41%** ± 5.05
Structural Similarity Index (SSIN)	**+9.55%** ± 3.46	**+3.86%** ± 1.45	**+4.26%** ± 2.13	**+11.6%** ± 4.01
Signal-to-Noise Ratio (SNR)	**+12.15%** ± 3.02	**+14.79%** ± 4.54	**+12.86%** ± 4.45	**+13.92%** ± 3.54
Peak Signal-to-Noise Ratio (PSNR)	**+9.97%** ± 2.1	**+13.6%** ± 3.97	**+11.32%** ± 2.16	**+13.59%** ± 3.53

In order to assess the results from the experimental data quantitatively, Table I presents the image quality metrics before and after applying the proposed edge detail preservation method to the original speckle reduction methods and their standard deviations. Table II presents the percentage mean change in image quality metrics after applying the proposed edge detail preservation method to the original speckle reduction methods and their percentage standard deviations. The p-values of statistical significance testing for the two sets of results over the 26 experiments were all significant at the 0.05 level, which supports the hypothesis that the reported changes in image quality metrics are statistically significant. The results indicate that the new edge detail preservation method significantly improves image quality metrics for all speckle reduction methods where error metrics (GAE, MSE, LMSE, NAE, and Minkowski error metrics) become lower and quality metrics (SNR, PSNR, Q, and SSIN) become higher. To illustrate the actual image quality metric values across different imaging experiments, Fig. 6 shows plots of three example metrics of LMSE, SSIN and Quality, where the metric values from the original speckle suppression alone were plotted as a colored solid line and the combination with the new edge detail preservation method were shown as 'x' marks with the same color. It can be noted that the different applications affect the outcome of speckle suppression techniques in general and that different techniques vary in their performance. The addition of the new edge detail preservation method still resulted in marked improvement across applications and techniques. This suggests its robustness and potential to meet the rigorous demands in real clinical use.

In order to further qualitatively demonstrate the advantage of using the new edge detail preservation method, a zoomed version of the outcomes from using the tissue-mimicking resolution phantom is presented in Fig. 7 where the resolution pins are compared between the outputs from the Lee method with and without the new method. The blurring in the original technique is evident and significant visual improvement is observed after using the new method.

For the ultrasound imaging data from public databases, Table III presents the image quality metrics before and after applying the proposed edge detail preservation method to the original speckle reduction methods and their standard deviations across all 3208 images. Also, Table IV presents the percentage mean change in image quality metrics after applying the proposed edge detail preservation method to the original speckle reduction methods and their percentage standard deviations. The results indicate that the new edge detail preservation method generally improves image quality metrics for all speckle reduction methods where most error metrics (GAE, MSE, LMSE, NAE, and Minkowski error metrics) become lower and quality metrics (SNR, PSNR, Q, and SSIN) become higher. However, the percentage mean change rates of image equality metrics improvement are lower than those in the experimental data particularly for quality metrics (SNR, PSNR, Q, and SSIN). This is most obvious with SRAD technique. This can be explained by the quantization effects on the calculations of the proposed method where edge detection accuracy can be significantly affected, especially for weak edges encountered inside tissues such as edges of blood vessels within the liver. Whereas the experimental data have a quantization level of 16 bits per pixel, the images from public databases come with only 8 bits per pixel, which is substantially lower. This indicates that the proposed method may be better suited to process the raw data rather than the formed, limited quantization ultrasound images.

The advantage of the new edge detail preservation method is that it recognizes the significant body of research already presents in the field of speckle reduction filtering and works to boost the performance of existing methods. This study demonstrated the effectiveness of combing the new method with four existing speckle reduction filters, but its generality and applicability with any other technique are readily evident from its block diagram. The improvement results presented should encourage broader adoption in this area.

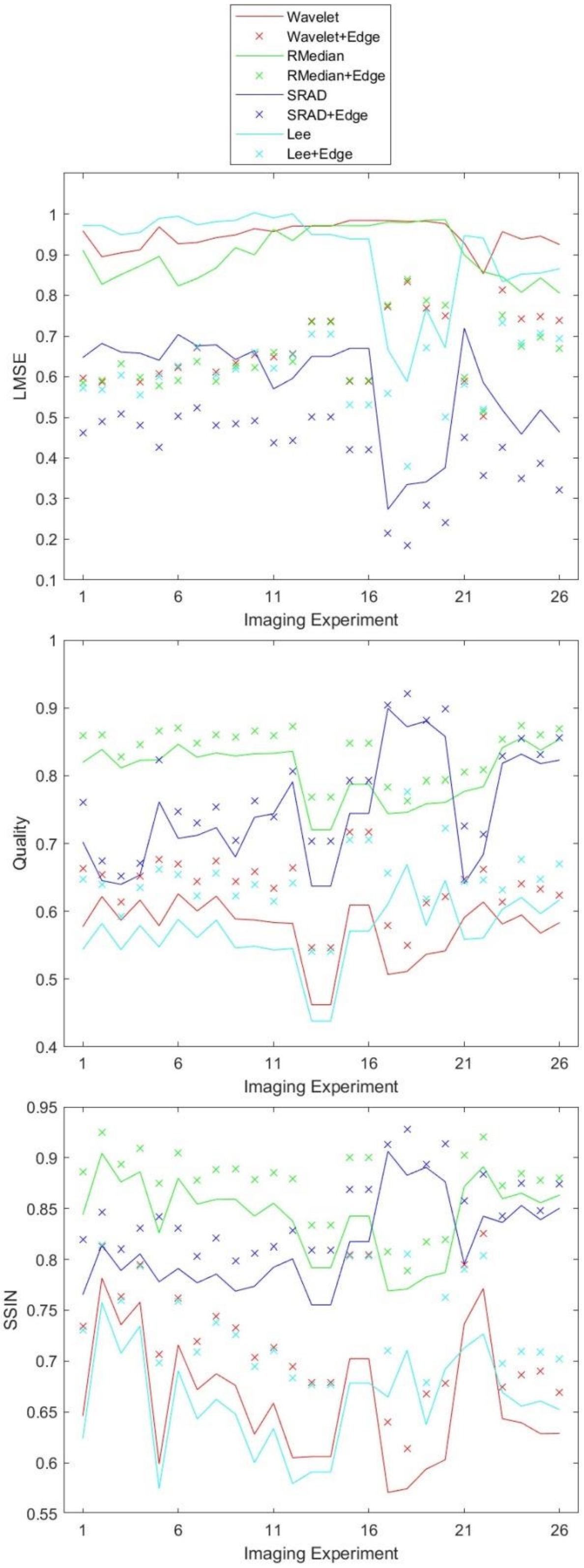

Fig. 6. Performance Comparison of Original Speckle Suppression Techniques with and without New Edge detail Preservation Method as Evaluated by Three Quantitative Image Quality Metrics across 26 Imaging Experiment.

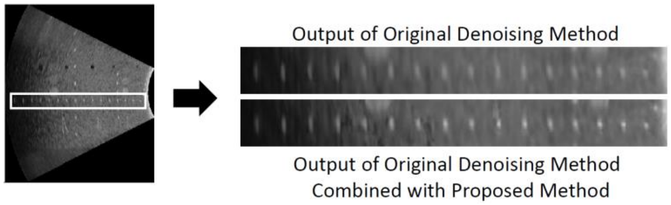
Output of Original Denoising Method
Output of Original Denoising Method
Combined with Proposed Method

Fig. 7. Qualitative performance comparison of example speckle suppression technique (Lee) with and without new edge detail preservation method where a zoomed part of the output for a tissue mimicking resolution phantom is magnified to demonstrate the improvement.

TABLE III. IMAGE QUALITY METRICS BEFORE AND AFTER APPLICATION OF PROPOSED EDGE PRESERVATION TO ORIGINAL SPECKLE REDUCTION METHOD, AND ITS STANDARD DEVIATION CALCULATED ACROSS ALL IMAGES IN BUSI AND ULTRASOUND CASES DATABASES

Quality Metric	**Wavelet**		**Relaxed Median**		**SRAD**		**Lee**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Geometric Average Error (GAE)	3.00 ± 0.76	2.77 ± 0.73	1.44 ± 0.33	1.63 ± 0.28	1.97 ± 0.36	1.94 ± 0.32	2.71 ± 0.53	2.49 ± 0.52
Mean Squared Error (MSE)	50.86 ± 26.16	50.09 ± 23.59	901.3 ± 97.52	521.88 ± 205.29	29.02 ± 7.79	27.70 ± 6.80	68.07 ± 19.59	58.38 ± 17.51
Laplacian Mean Squared Error (LMSE)	0.20 ± 0.04	0.15 ± 0.08	0.97 ± 0.07	0.55 ± 0.08	0.14 ± 0.13	0.11 ± 0.1	0.25 ± 0.13	0.17 ± 0.08
Normalized Absolute Error (NAE)	0.1 ± 0.01	0.09 ± 0.01	0.11 ± 0.01	0.08 ± 0.01	0.07 ± 0.05	0.07 ± 0.04	0.10 ± 0.01	0.09 ± 0.01
Minkowski Error Metric (β=1)	5.42 ± 1.44	5.07 ± 1.39	5.87 ± 0.67	4.70 ± 1.03	3.38 ± 0.72	3.76 ± 0.64	5.35 ± 1.07	4.94 ± 1.03
Minkowski Error Metric (β=3)	8.99 ± 2.13	8.41 ± 2.07	59.91 ± 2.78	46.35 ± 8.47	6.54 ± 0.74	6.38 ± 0.68	10.88 ± 1.29	10.00 ± 1.30
Minkowski Error Metric (β=4)	10.5 ± 2.48	9.79 ± 2.41	85.31 ± 3.46	68.26 ± 11.14	7.57 ± 0.75	7.37 ± 0.70	13.71 ± 1.50	12.51 ± 1.53
Universal Quality Index (Q)	0.67 ± 0.09	0.68 ± 0.09	0.86 ± 0.05	0.88 ± 0.06	0.76 ± 0.06	0.75 ± 0.07	0.72 ± 0.06	0.74 ± 0.07
Structural Similarity Index (SSIN)	0.85 ± 0.06	0.87 ± 0.05	0.93 ± 0.04	0.95 ± 0.03	0.88 ± 0.04	0.89 ± 0.03	0.82 ± 0.05	0.84 ± 0.05
Signal-to-Noise Ratio (SNR)	23.30 ± 1.58	23.89 ± 1.71	10.45 ± 1.47	13.2 ± 1.85	25.92 ± 0.89	26.10 ± 0.85	22.17 ± 0.82	22.88 ± 0.96
Peak Signal-to-Noise Ratio (PSNR)	31.21 ± 2.20	31.85 ± 2.29	18.53 ± 0.49	20.48 ± 1.76	33.65 ± 1.20	34.02 ± 1.08	29.67 ± 1.18	30.57 ± 1.33

TABLE IV. AVERAGE PERCENTAGE ALTERATION IN IMAGE QUALITY METRICS FOLLOWING APPLICATION OF PROPOSED EDGE PRESERVATION TO ORIGINAL SPECKLE REDUCTION METHOD AND PERCENTAGE STANDARD DEVIATION ACROSS ALL IMAGES IN BUSI AND ULTRASOUND CASES DATABASES.

Quality Metric	Wavelet	Relaxed Median	SRAD	Lee
Geometric Average Error (GAE)	**-7.78%** ± 2.92	**+12.69%** ± 7.59	**-1.7%** ± 2.32	**-7.93%** ± 3.45
Mean Squared Error (MSE)	**-11.90%** ± 6.42	**-42.10%** ± 16.51	**-4.56%** ± 4.28	**-14.24%** ± 8.68
Laplacian Mean Squared Error (LMSE)	**-24.61%** ± 48.00	**-43.57%** ± 20.61	**-21.78%** ± 56.35	**-30.55%** ± 52.64
Normalized Absolute Error (NAE)	**-6.59%** ± 2.44	**-21.12%** ± 10.59	**-1.43%** ± 2.09	**-7.75%** ± 3.14
Minkowski Error Metric (β=1)	**-6.45%** ± 2.71	**-19.86%** ± 7.19	**-1.71%** ± 2.33	**-7.60%** ± 3.44
Minkowski Error Metric (β=3)	**-6.44%** ± 2.2	**-22.63%** ± 11.51	**-2.44%** ± 1.63	**-8.04%** ± 4.49
Minkowski Error Metric (β=4)	**-6.79%** ± 2.15	**-19.99%** ± 10.77	**-2.64%** ± 1.45	**-8.77%** ± 4.74
Universal Quality Index (Q)	**+2.40%** ± 6.53	**+1.77%** ± 4.77	**-1.09%** ± 5.63	**+2.93%** ± 4.89
Structural Similarity Index (SSIN)	**+2.61%** ± 4.10	**+1.79%** ± 3.97	**+1.04%** ± 4.16	**+11.6%** ± 4.36
Signal-to-Noise Ratio (SNR)	**+2.54%** ± 1.07	**+26.33%** ± 14.43	**+0.68%** ± 0.58	**+3.22%** ± 1.66
Peak Signal-to-Noise Ratio (PSNR)	**+2.05%** ± 0.84	**+10.5%** ± 7.69	**+1.11%** ± 0.50	**+3.04%** ± 1.35

Even though the proposed method is meant to be applied as a tool to complement speckle reduction methods rather than compete with them, it is important to demonstrate that its performance enhancement with classical methods compare well with recent techniques to show its potential. Comparing the presented results to those of [34] using real ultrasound data, the best reported values of PSNR and SSIM are 31.47 and 0.8026 respectively, whereas these same metrics reach 33.25 and 0.87 in the proposed method for experimental data and 34.02 and 0.95 for data from publicly available databases. This particular study shares the utilization of raw ultrasound imaging data as the input to the technique like the proposed method, but the number of images used in that study was reported to be only 20 images out of 366 images that were available in their data source [34], which is much lower than the number of experimental images used in this study of 260 images. Furthermore, simulated speckle noise was added artificially to such real images, which makes such testing data artificial. On the other hand, the study in [37] reported best PSNR and SSIM values of 38.1952 and 0.9770 respectively, which are significantly higher than this work. However, close inspection of the methodology used in that study reveals that such high values were obtained using simulated low variance speckle patterns superimposed on publicly available ultrasound images with very high SNR (small depth of penetration for neural ultrasound images and low attenuation from blood within cardiac images). The reported best results for PSNR and SSIM in that same study from higher speckle variance were 31.3849 and 0.9046 respectively, which are outperformed by the proposed method when applied to publicly available ultrasound images. Furthermore, in [38] the reported best values for PSNR and SSIM were 34.89 and 0.89 respectively, which are again outperformed by the proposed method for publicly available ultrasound images. Hence, the comparison with recent techniques indicates that the proposed method has potential to enhance classical, explainable speckle reduction methods to perform well against more recent deep learning-based methods while maintaining lower complexity.

Given that the new method adds more steps to existing speckle reduction filtering, a concern arises about whether this will affect the real-time performance that is considered very important in ultrasound imaging. In order to estimate the computational complexity of the added blocks in the new method, we need to consider the blocks used to do Canny edge detection (dominated by convolutions), 2D Gaussian filtering (convolution), and final edge detail restoration (addition). For an ultrasound image acquisition M sticks and N samples per line, the combined computational complexity of efficient implementations of these blocks will be $\boldsymbol{O}(MN\log_2(MN))$. This is close to the same order of computations as the image reconstruction process involving scan conversion and interpolation of raw data but with M being the second dimension of the image rather than the smaller number of sticks. Hence, adding the proposed method to the processing chain is not expected to pose any burden for real-time performance especially with current high processing capabilities available in modern digital ultrasound imaging systems. The added complexity of different speckle reduction techniques to be used in combination with the proposed method varies widely across different techniques. To investigate this issue further, we conducted several experiments on Matlab to measure the computation time for the four speckle reduction techniques used in this work along with that of the added processing to implement the proposed method and also the image reconstruction from experimental data for different images sizes. The computational time results are shown in Fig. 8. As can be observed, the computational time of the proposed method scales fairly adheres to the theoretical estimate where it is close to the reconstruction time for smaller image sizes and becomes significantly lower for the commonly used image size of 512. The image reconstruction time increases at a much higher rate at this size because of the much larger number of points in the sector format image that need to be interpolated compared to those at smaller sizes. Furthermore, the proposed method has a significantly lower computational time compared to all speckle reduction methods except the Lee method at this size. Even with the techniques having the largest computation time (Wavelet method), the total computational time needed of 19 ms (Wavelet method) + 11 ms (image reconstruction) + 3 ms (proposed method) = 33 ms at image size of 512×512, offers real-time performance of 30 frames/s on Matlab under Windows operating system without parallel processing or GPU computation. This indicates that real-time performance requirements will be met or exceeded with the dedicated high performance processing platforms used in modern ultrasound imaging systems.

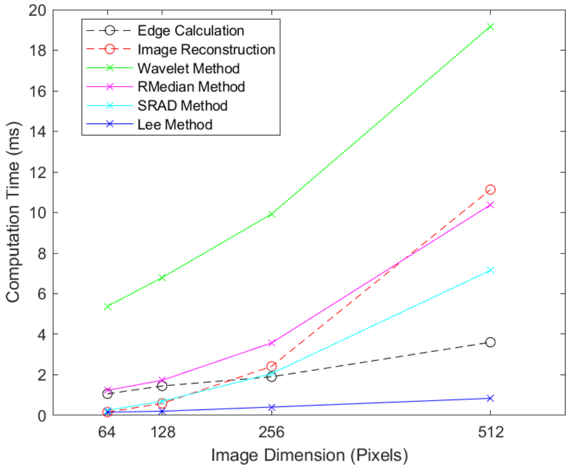

Fig. 8. Computational time for different speckle reduction techniques compared to additional processing for proposed method and image reconstruction for different image sizes.

V. Conclusion

This work introduces a novel method designed to augment existing speckle suppression techniques by preserving the edge detail content of images. The process initiates by extracting the edge detail content from the original image. Instead of directly applying the traditional method to the speckle suppression filtering technique, the edge detail content is subtracted from the original image before undergoing the filtering process. Subsequently, this edge detail content is incorporated into the output of the filtering, culminating in the generation of the final image. Experimental validation of this new method was conducted through 26 imaging experiments as well as 3208 ultrasound images from publicly available databases, employing four representative speckle reduction filters. Real ultrasound imaging data were used to assess the method's performance. Evaluation involved both qualitative comparisons of image appearances and quantitative analyses using eleven image quality metrics. The results affirm the effectiveness of the proposed method and underscore its potential to enhance diagnostic accuracy. Future work includes use for other imaging modalities such as low field MRI or nuclear medicine and combination with other despeckling methods.

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A Neuro-Genetic Security Framework for Misbehavior Detection in VANETs

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Abstract*—Genetic Algorithm (GA) is an excellent optimization algorithm which has attracted the attention of researchers in various fields. Many papers have been published on works done on GA, but no single paper ever utilized this algorithm for misbehavior detection in VANETs. This is because GA requires manual definition of fitness function and defining a fitness function for VANETs is a complex task. Automating the creation of these fitness functions is still a difficulty, even though studies have found several successful applications of GA. In this study, a neuro-genetic security framework has been built with ANN classifier for detecting misbehavior in VANETs. It leverages a genetic algorithm for feature reduction with ANN as a dynamic fitness function, considering both node behaviors and contextual GPS data. Deployed at the Roadside Unit (RSU) level, the framework detects misbehaving nodes, broadcasting alerts to RSUs, Central Authority and the vehicles. The ANN based fitness function has been employed in GA that enabled the GA to select the best results. The 10- fold CV used enabled the whole system to be unbiased giving a precision accuracy of 0.9976 with recall and F1 scores as 0.9977, and 0.9977 respectively. Comparative evaluations, using the VeReMi Extension dataset, demonstrate the framework's superiority in precision, recall, and F1 score for binary and multiclass classification. This hybrid genetic algorithm with ANN fitness function presents a robust, adaptive solution for VANET misbehavior detection. Its context-aware nature accommodates dynamic scenarios, offering an effective security framework for the evolving threats in vehicular environments.

Keywords*—*VANET security; genetic algorithm; ANN fitness function; misbehavior detection; hybrid detection

I. Introduction

Modern technology advancements and high transportation expectations have caused the global automobile utilization rate to rise quickly [1]. The transport industry is dealing with a variety of issues due to the quick rise in the number of automobiles and the limited space in the infrastructure of roads, including a spike in traffic accidents, prolonged traffic jams, damage to public property and human life, etc. To address these issues and improve the efficiency of the transportation sector, Vehicular ad hoc networks (VANETs) emerged as a particular kind of mobile ad hoc network (MANET) [2] in which mobile nodes are vehicles such as cars, trucks, buses, and motorcycles etc. Vehicles follow the design of the road, corresponding to traffic regulations and flow restrictions rather than moving at random. Vehicles exhibit different speeds, and their movement and their behavior are impacted by the traffic signals, road signs, and other vehicles. The density of these networks or topology of these networks varies very rapidly, depending on the area, the time of day, and recent occurrences (like traffic jams or accidents) [3].

Around the year 2000, Vehicular Ad-hoc Networks (VANETs) were the subject of investigation for many research laboratories [4]. VANET was first used to improve road traffic safety and lower the number of accidents and traffic jams [5]. Today it covers numerous integrated services employing other technologies in addition to the basic functionality provided by VANET architecture, indicating a significantly wider application [6].

As shown in Fig. 1, the key constituents of VANETs are typically Trusted Authority (TA), Roadside Units (RSUs), and Onboard Units (OBUs). As the only component in a VANET that can be completely trusted, TA oversees monitoring the whole setup and changing the parameters for the other components. RSU, on the other hand, is set up along roadsides as wireless infrastructure to link cars to TA. Every vehicle has an OBU, a wireless device that processes, transmits, and receives messages (such as road status, condition, and so on) from other cars [7]. Vehicles can communicate with each other through vehicle-to-vehicle (V2V) communication in VANETs as well as with infrastructure through RSUs through vehicle-to-infrastructure (V2I) communication. Every vehicle in the VANET transmits data messages and safety messages every 100 to 300ms to the vehicles in range in accordance with dedicated short-range communications (DSRC) requirements [8]. The transmission of data and safety-related information by vehicles in an open-access setting creates security and privacy challenges for VANETs. If appropriate precautions are not taken, attackers may utilize user information to launch a variety of attacks that might be harmful to the network and its users.

Predictable mobility patterns, a large network size, frequent disconnections, a high rate of topology changes, and strict delay constraints are only a few of the distinguishing characteristics of VANETs that make it extremely prone to a variety of misbehaviors. Even though VANET research has been ongoing for more than a decade, there are still many open challenges, including ineffective QoS, uneven flow traffic, security and privacy concerns, poor resource utilization, and inefficient information distribution [9].

Additionally, there is need to apply various contextual information to enhance the ability to differentiate between nodes that are genuinely malicious and those that exhibit anomalous behavior for contextual reasons. Fig. 2 provides a great illustration of misbehavior scenario in VANETs. The vehicle v1 drops packets in both scenarios, leading most of the current security systems to treat it as a misbehaving node without doing any more research. But taking a closer look at the setting in which packet loss occurs in, it is found that in case (a), v1 drops packets likely due to the busy channel; in case (b), no external factor prevents it from forwarding those packets, indicating that v1 is acting maliciously. This example makes it abundantly evident that context could be crucial in identifying misbehaving nodes in VANETs.

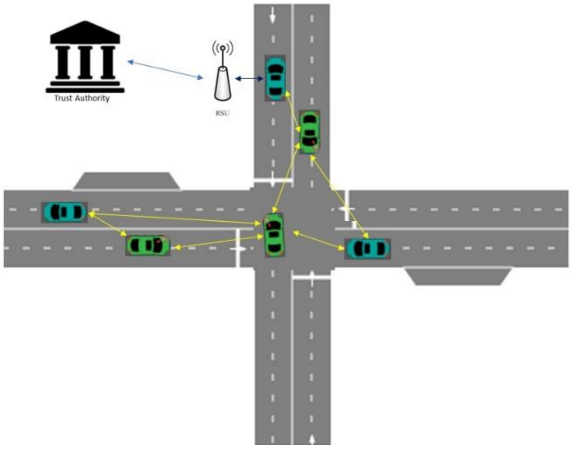

Fig. 1. Structure of VANET.

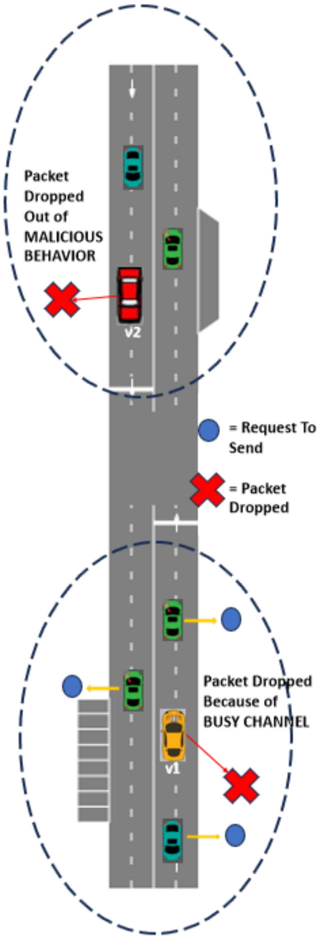

Fig. 2. Misbehavior example scenario.

In this paper, a context aware framework is proposed for detecting misbehavior in VANETs. In the proposed framework, both node behaviors (taken from BSM messages) and contextual information (taken from GPS data) are represented as features in the feature vector to train a genetic algorithm, with an artificial neural network (ANN) serving as its fitness function. The genetic algorithm takes the feature vector as input, dynamically reducing features based on ANN accuracy, and subsequently classifies whether a node exhibits malicious behavior. This hybrid genetic algorithm could offer a solution by combining the strengths of genetic algorithms, which excel in optimization and exploration of solution spaces, with ANN, creating a more dynamic and effective security framework for VANETs.

The main contributions of the study are to:

- Propose a security framework for misbehavior detection for VANETs using hybrid genetic algorithm with ANN fitness function.
- Compare multiple ML algorithms to be used as fitness function for genetic algorithm for better misbehavior detection.
- Compare the proposed framework with the existing ones for evaluation of the results.

Section II of this paper presents the overview of the existing works done in the field; Section III presents the proposed framework, including the communication architecture and the processing steps. Section IV discusses the simulation setup and results that include a comprehensive exploration of the framework, and a series of experiments that demonstrate the framework's effectiveness in detecting misbehaviour across a range of scenarios. Furthermore, it provides evidence of the framework's superiority over traditional machine learning models and existing misbehaviour detection methods, underscoring the critical role of context-awareness and the ANN-based fitness function in VANET security. Section V presents the discussion of the results, and the conclusion of the paper is provided in Section VI.

II. Existing Works

Over the past years, several security methods have been investigated to identify and address these misbehaviors in VANETs. The proposed Trust-Based Event Detection Algorithm (TB-EDA) compares the trust values of the neighboring cars of a node with the threshold trust value measured to identify misbehaviors [10]. In study [11], the authors introduced the Vehicular Reference Misbehavior dataset (VeReMi) to assess various misbehavior detectors. They also assessed different detectors on their datasets using metrics such as precision and recall. While misbehavior detection systems based on rules or specifications can provide security against known attacks, they lack the ability to identify unknown attacks.

To enhance robustness against Sybil attacks in VANETs, [12] proposed anonymous authentication and Sybil attack detection protocol. In a broader framework employing subjective logic, [13] improved two position verification mechanisms for misbehavior detection. The ML-based

Intrusion Detection System (IDS) proposed in [14] focuses on thwarting spoofing attacks using a probabilistic cross-layer approach in a VANET consisting of Electric Vehicles. The research in [15] presented SVM-based IDS for VANETs, incorporating an enhanced penalty function to strengthen the classifier's regularization. The study in [16] suggested ML-based IDS for VANETs, where XGBoost demonstrated superior performance in binary class and multi-class classification problems. The research in [17] introduced a data-centric approach to identify position falsification attacks, employing machine learning (ML) algorithms. The proposed method combines information from two consecutive Basic Safety Messages (BSMs) for both training and testing purposes.

The majority of these security solutions use one or more pre-established, predefined thresholds to identify abnormal nodes from regular ones. However, it is not possible to determine a single set of thresholds that perform effectively in every situation due to the very dynamic nature of VANETs. However, as the use of machine learning solutions for misbehavior detection is rising, the studies have showcased more dynamic and adaptive approaches for VANETs. But there is still a gap: there are limitations of traditional machine learning approaches in handling the dynamic and complex nature of VANET security. While machine learning has shown promise, it may struggle with the rapidly changing and unpredictable nature of vehicular environments and the ever-evolving threats. It is proposed that hybrid algorithms could fill this gap by introducing a more adaptive and robust approach by combining the best of two or more algorithms for identifying the border between normal and misbehaving nodes automatically.

III. Proposed Framework

A. Proposed Architecture

Fig. 3 presents the communication architecture of the proposed framework. Most studies of misbehavior detection in VANETs applied misbehavior detection in On Board Units (OBUs) of individual vehicles. Keeping in mind that the communication range of RSUs is much broader than the communication range of vehicles [18], in the proposed scheme, our detection framework will be deployed at the RSU level. RSUs have greater computing capacity available for misbehavior detection than vehicle OBUs, which are more resource restricted. Notifying legitimate vehicles of a possible attack even before they come into communication range of the misbehaving vehicle is another advantage of the suggested approach. It will work as follows: Every vehicle gets its credentials for communication during the registration process with the authority (CA). When a vehicle sends the Basic Safety Messages (BSMs), are received by all vehicles and RSUs within the sender vehicle's communication range. These BSMs along with the GPS data are used by the RSUs for identifying the misbehaving nodes through the hybrid detection module of the proposed framework. On detecting misbehavior, an alert is generated and is broadcasted to the vehicles and other RSUs in the communication range. When such alert is received by any vehicle, it updates the misbehaving node’s data into its local OBU to prevent future communication. The RSUs broadcast the alert to their respective vehicles in range and in such a way alert reaches the other vehicles through the network of RSUs.

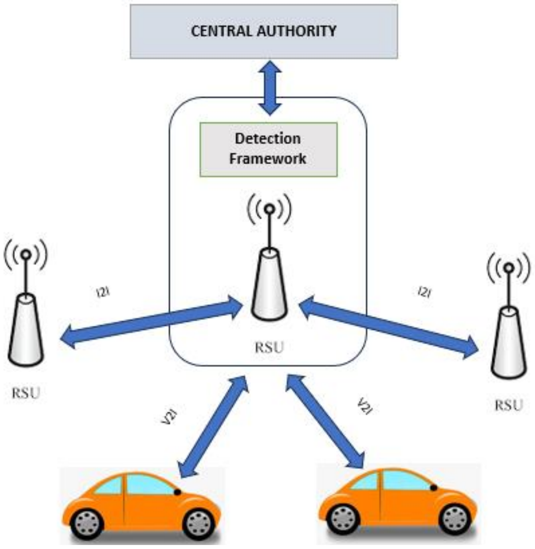

Fig. 3. Communication architecture.

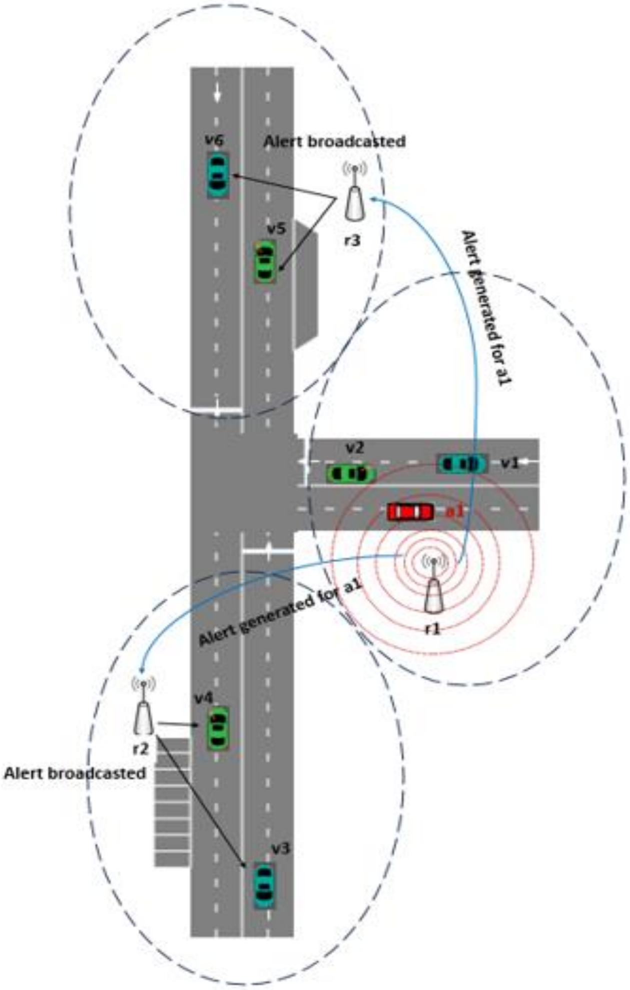

Fig. 4. VANET example scenario.

An example scenario is provided in Fig. 4 where v1, v2, v3, v4, v5, v6 are legitimate vehicles, a1 is a misbehaving vehicle, r1, r2, r3 are RSUs. Vehicle a1 is detected misbehaving by r1 which then broadcasts the alert to vehicles and RSUs in range. v1 and v2 being in range get this alert directly while v3, v4, v5 and v6 get this alert through the RSUs r2 and r3. In this way vehicles that are not even in range get the alert and are prevented from being attacked or misled. After detection of misbehavior, additional action may be taken by the CA depending on its own policy and procedures, which are not in the scope of this study.

B. Proposed Framework

The core contribution of this study is the framework for misbehaviour detection for the VANETs. The performance efficiency and the effectiveness of the suggested security framework are both significantly impacted by the entire features that are employed by the detection system. Detection accuracy, computational time and memory requirements have been identified as the primary factors for which the reduction in the total number of features is required by the system.

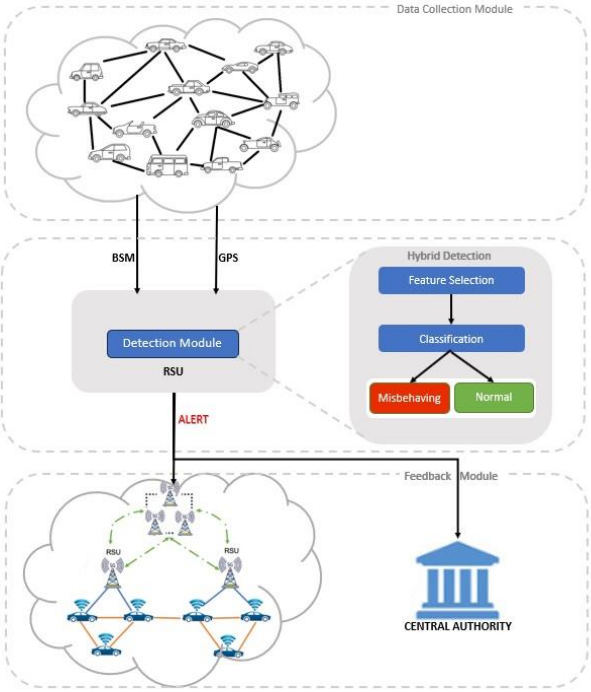

Fig. 5. Proposed Framework

The proposed framework (see Fig. 5) consists of three modules which include:

- Data collection module: This module collects the behavioural data and the contextual data from the network and sends it to the detection module.
- Hybrid Detection: This module primarily consists of a Genetic Algorithm model, which analyses the data, filters out the irrelevant characteristics, and reconstructs a low-dimensional feature dataset then uses supervised algorithms to categorize traffic, judge if it is being subjected to an attack, and decide whether to provide a warning in response to the findings.
- Feedback module: Using the machine's output status and alarm information, this module modifies its operations.

C. Processing Steps

There are two primary phases to implementing the suggested framework: dataset preparation and hybrid classification.

1) Dataset preparation: Every BSM has a unique message ID, the sender's ID, and a time stamp showing when it was sent in addition to the pertinent status information. A labelled VeReMi Extension dataset [19] was used for training and testing our proposed framework. It consists of message logs for each vehicle, which include BSM messages (labelled as type=3) received from other vehicles via DSRC, as well as GPS information (labelled as type=2) about the vehicle. There is one ground truth file and several unique log files for every simulation, which include the BSMs that each vehicle received. As a result, there are exactly as many log files as there are receivers. Every BSM is logged in several distinct log files as it is received by numerous vehicles. First to get rid of redundant information, the processing of the merged log files was carried out. After that, the combined log files and the ground truth file are merged, and a labelled dataset is produced for every simulation using this combined file.

2) Hybrid detection: After the required labelled dataset is ready, Artificial Neural Network (ANN) fitness function based Genetic Algorithm (GA) was used for feature reduction and detecting misbehavior.

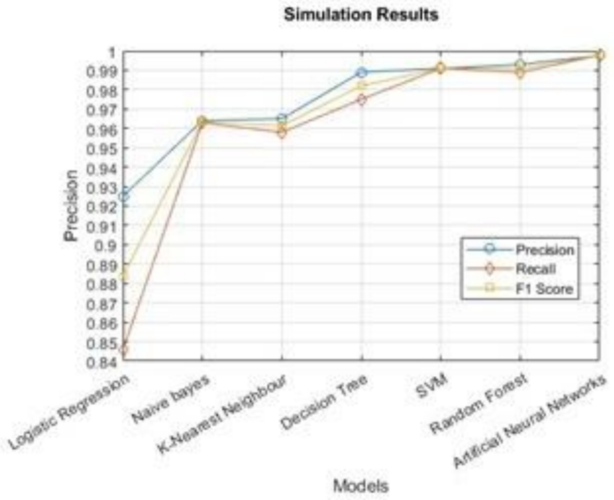

Fig. 6. Simulation Results for different fitness functions

a) Genetic Algorithm with ANN: Genetic Algorithm is used to solve a problem from a pool of potential solutions. GA is based on a fitness function, through which the generated candidates are iteratively developed, modified, and chosen for survival. Fitness functions are often manually constructed heuristics that rank candidate solutions according to how near they are to being accurate, with the candidate solutions that score higher being more likely to be picked for next generations [20]. Automating the creation of these fitness functions is still a difficulty, even though studies have found several successful applications of GA. In [21], authors have proposed an approach called NetSyn to automatically generate these fitness functions by representing their structure with a neural network. While they investigated this technique in the context of Machine Programming, they presented the technique to be applicable and generalizable to other domains also. Using that approach various classification algorithms have been explored that could be used as fitness function for GA. Among these, the following seven classifiers were selected: ANN, K-Nearest Neighbor (kNN), Random-Forest, Decision tree, Logistic Regression, Support Vector Machine (SVM) and Naïve Bayes, and compared the results (See Fig. 6). The results show that ANN yielded the best results among all. Algorithm 1 outlines the use of Genetic Algorithm with ANN Fitness function. The parameters used in GA are provided in Table I and the flowchart for the process is shown in Fig. 7.

Algorithm 1: Genetic Algorithm with ANN

```
BEGIN
Random initialization of population
For each generation (t) from 1 to max_generation:
    For each solution: evaluate fitness of each solution in the population
            Split the solution into 10 folds for cross-validation into ANN.
            Calculate and return the average accuracy as the ratio of correct predictions to the total number of predictions
    End
    Display progress information every 10 generations (optional).
    Sort the solutions based on their fitness.
    Select the two best solutions for reproduction.
    Apply Genetic Algorithm operators (crossover and mutation) to create new solutions.
    Update the population with the new solutions.
END
```

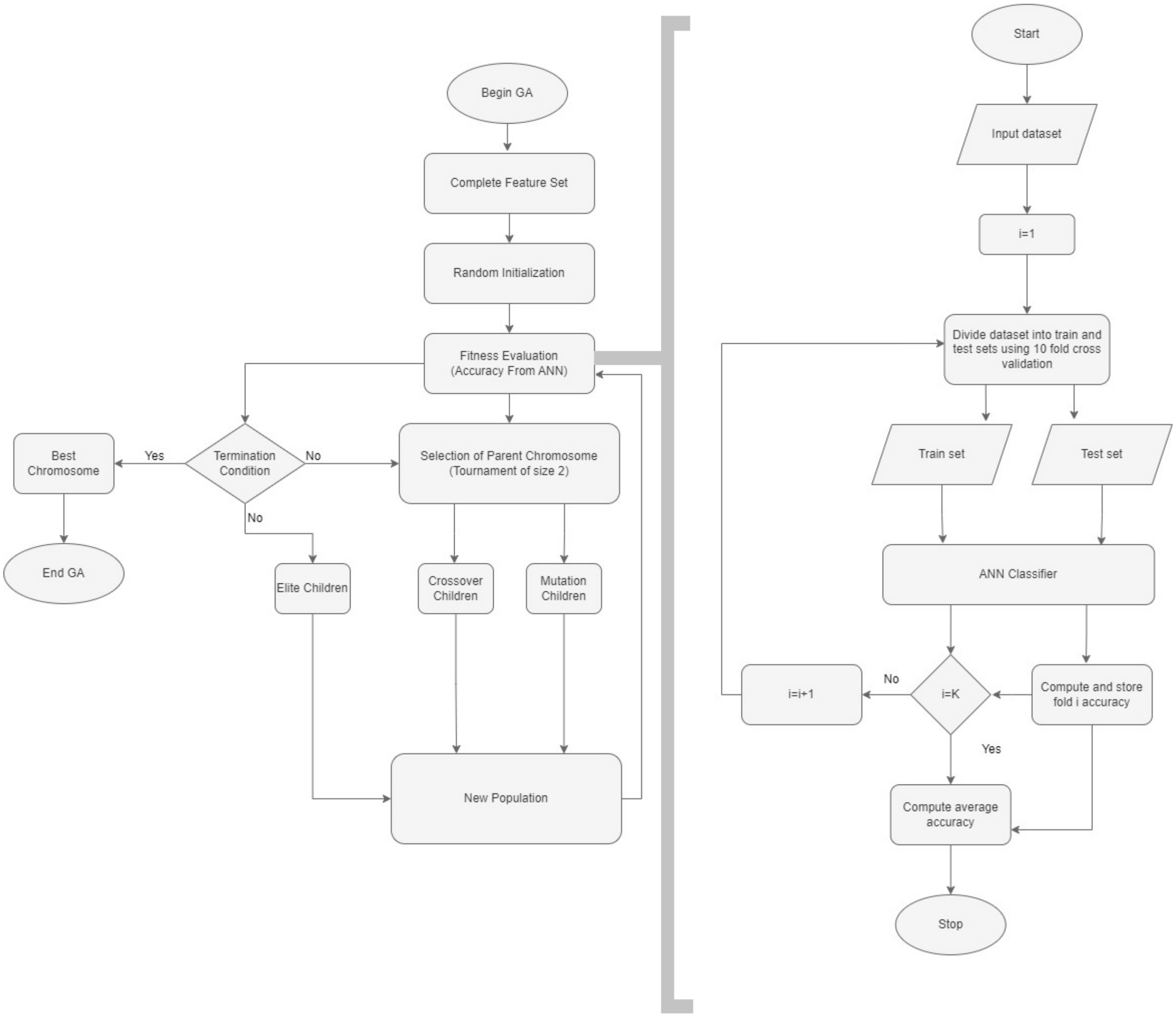

Fig. 7. Simulation Results Genetic Algorithm-based Feature Selection.

b) Cross-validation: To prevent the model from overfitting and effectively measure its accuracy, the entire dataset was split into k folds of train and test sets, with one split serving as the validation set and the remaining k-1 split as training set. Depending on the dataset, the value of k typically ranges from 5 to 10, and in this implementation, k = 10 has been used.

TABLE I. PARAMETERS USED IN GA

Parameter	Value
Genome length	33
Population size	300
Number of generations	500
Mutation	Uniform Mutation
Mutation Probability	0.1
Crossover	Arithmetic Crossover
Crossover Probability	0.8
Fitness Function	ANN-Based Classification Accuracy
Selection scheme	Tournament of size 2
Elite Count	2

IV. SIMULATION SETUP AND RESULTS

A publicly accessible VeReMi Extension dataset [19] has been utilized for training and testing the framework, to evaluate the suggested framework and guarantee fair comparisons. Using common metrics on this dataset, the suggested technique was evaluated and compared its results with those of previous approaches.

Information from both normal and misbehaving cars make the VeReMi Extension an imbalanced dataset [22]. The measures listed in Eq. (1) through Eq. (3) have been utilized for evaluating and comparing the performance of the proposed framework because accuracy by itself is insufficient as a metric for an imbalanced dataset. The misbehaving vehicle is indicated by a 1 in our dataset, whereas the genuine vehicle is shown by a 0.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (1)$$

$$Recall \quad = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (2)$$

$$F1\ Score \ = \ 2 * \frac{Precision * Recall}{Precision + Recall} \quad (3)$$

The implementation was carried out in two ways: binary classifications, to simply classify vehicles as normal or misbehaving and multiclass classification, to identify the specific misbehaviour being carried out.

A. Results

The results of the proposed framework's binary classification can be seen in Fig. 8. 99.99% of the cases may be identified accurately when utilizing the binary classification approach. When the ROC is analysed, the framework's good measure of separability is shown by an AUC (area under the curve) that is close to 1. With binary classification the framework has shown the precision, recall and F1 scores as 0.9999 for all three metrics.

The results of the multiclass classification of the proposed framework are displayed in Fig. 9. When employing the multiclass classification approach, the proposed framework has 99.76% detection accuracy. Since the AUC is close to 1, the framework is also performing quite well when it comes to multiclass categorization. With multiclass classification, the proposed framework has shown precision, recall and F1 scores as 0.9976, 0.9977, and 0.9977 respectively.

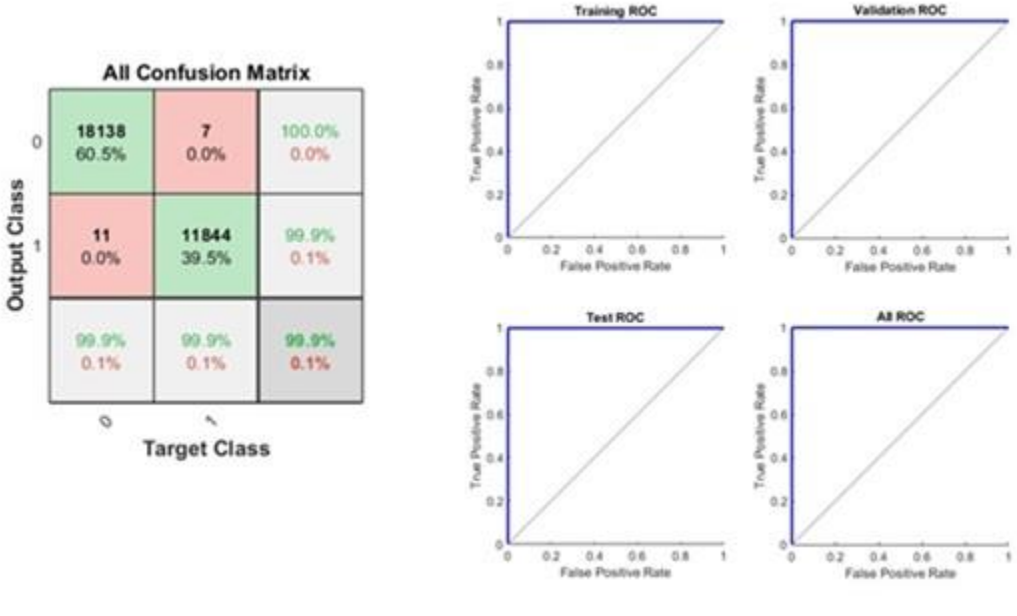

Fig. 8. Confusion matrix (left) and ROC (right) for binary classification.

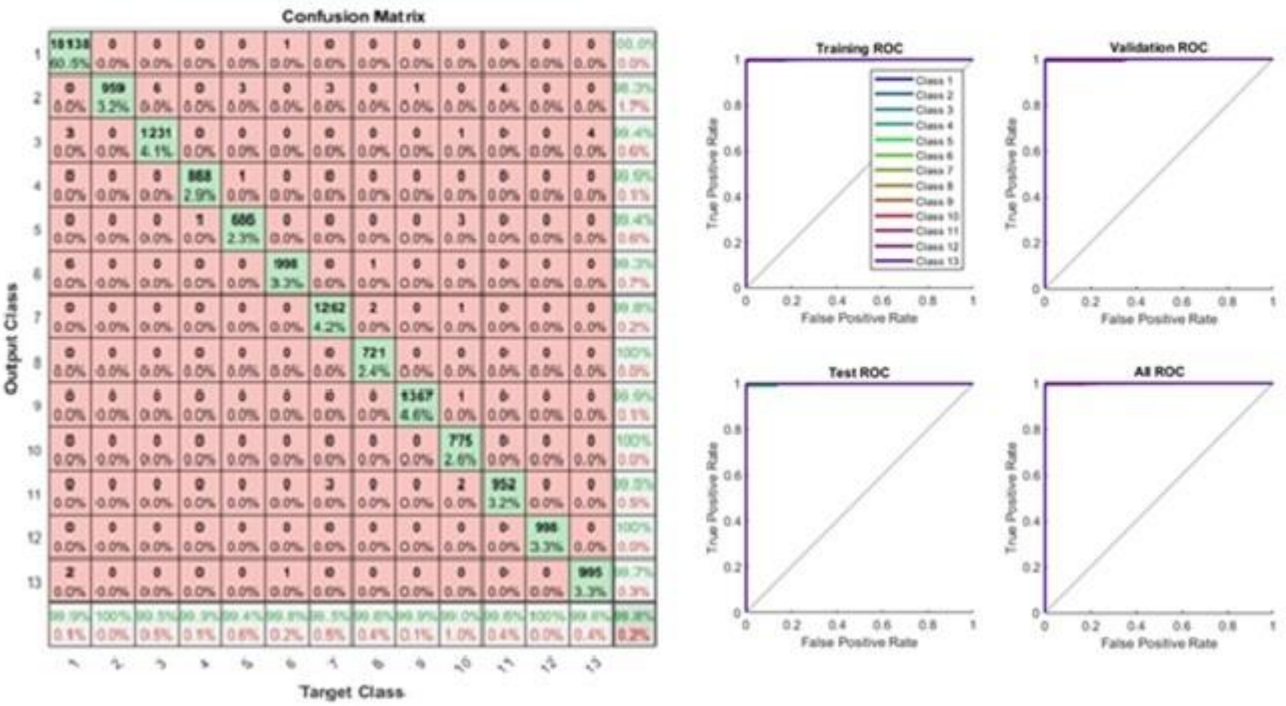

Fig. 9. Confusion matrix (left) and ROC (right) for multiclass classification.

B. Performance Evaluation with Varying Misbehaving Node Densities

Total five datasets were created with varying percentages of misbehaving nodes (10%, 20%, 30%, 40%, and 50%), and evaluated for the framework's performance under various misbehavior node densities. The simulation's outcomes are displayed in Fig. 10. The findings demonstrated that the framework demonstrated 100% accuracy with precision, recall, and F1 score all pointing to 1 when the proportion of misbehaving nodes was just 10% of the total number of nodes. The accuracy, recall, and F1 score values decreased as more and more misbehaving nodes were added to the dataset. Though the framework's performance was worse at 50% misbehaving nodes than in the 10% case, it still demonstrated 0.9967 recall, 0.9966 F1 score, and accuracy.

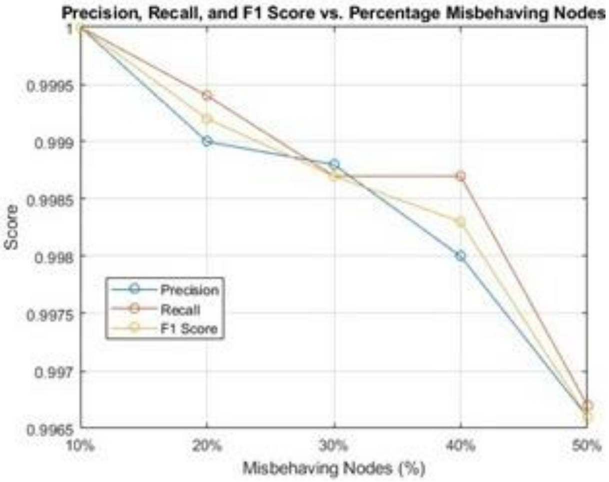

Fig. 10. Simulation Results for different node densities.

This demonstrates that even in the worst-case situations, where the fraction of misbehaving nodes is 50% of all nodes, our methodology is producing good outcomes.

C. Comparison with Existing Works

Table II presents a comparison between the existing works and the accuracy, recall, and F1 scores achieved using our proposed framework. The results make it evident that, in comparison to all other frameworks, Paper 4 [24] has extremely poor accuracy, recall, and F1 score values. While Paper 1 [23] had a high accuracy value of 0.9999 and performed comparable to the suggested model, it had a somewhat lower F1 Score and recall value. When it came to multiclass classification, the suggested model outperformed the other methods, with classifications showing 0.9976, 0.9977, and 0.9977 precision, recall, and F1 scores, respectively. When it came to binary classification, the framework displayed 0.9999 precision, recall, and F1 scores.

TABLE II. COMPARISON WITH EXISTING WORKS

Paper	Precision	Recall	F1 Score
Proposed Framework (with Binary Classification model)	0.9999	0.9999	0.9999
Proposed Framework (with Multiclass Classification model)	0.9976	0.9977	0.9977
Paper 1 [23]	0.9999	0.9554	0.977144
Paper 2 [11]	0.9886	0.8277	0.901023
Paper 3 [17]	0.988	0.99	0.988999
Paper 4 [24]	0.887	0.616	0.727069
Paper 5 [25]	0.978	0.932	0.954446

V. Discussion

The results of this study align closely with the theoretical framework presented in the introduction. The use of Genetic Algorithm (GA) with an Artificial Neural Network (ANN) fitness function for misbehavior detection in Vehicular Ad-hoc Networks (VANETs) is supported by the findings, which demonstrate high accuracy and robustness across different scenarios. This alignment validates the theoretical underpinnings of using a hybrid genetic algorithm approach for effective misbehavior detection in VANETs. The results of this study have several important implications for theory, practice, and future research. From a theoretical perspective, the success of the GA-ANN framework underscores the importance of context-awareness in misbehavior detection, as demonstrated by the use of GPS data and node behaviors as features in the classification process. Practically, this framework offers a robust and adaptive solution for VANET security, capable of detecting misbehaving nodes with high accuracy and efficiency. Compared to existing works in the field, the proposed GA-ANN framework demonstrates superior performance in terms of accuracy, precision, recall, and F1 scores. This highlights the effectiveness of the hybrid genetic algorithm approach in addressing the challenges of misbehavior detection in VANETs. The framework also outperforms existing methods in terms of adaptability to dynamic scenarios and robustness against evolving threats.

One of the key strengths of this study is the use of a comprehensive dataset and rigorous evaluation methodology, including 10-fold cross-validation, to assess the performance of the framework. However, one limitation is the reliance on simulated data, which may not fully capture the complexities of real-world VANET environments. Future research could involve testing the framework in real-world settings to validate its effectiveness further.

VI. Conclusion

This study presents a novel approach to detect misbehavior in VANETs using Genetic Algorithm with Artificial Neural Networks. Through the implementation of the misbehavior detection framework in the RSUs, which may broadly disseminate this information with other RSUs and vehicles, the proposed solution moves the computational burden from vehicles (OBUs). In contrast to existing methods, the proposed strategy uses ANN based fitness function in Genetic Algorithm. It was discovered after comparing several ML algorithms for fitness evaluation that ANN produces the best results.

The performance of the proposed framework was also compared with the existing solutions that have been published in the literature. The collected findings show that, in terms of precision, recall and F1 score, the suggested framework consistently outperforms the existing approaches across a variety of misbehavior types. Developing strong frameworks that can identify various misbehaviors using various GPS and BSM characteristics (such as heading, acceleration, and speed) is essential for safe VANET functioning.

Future research directions could focus on further enhancing the framework's performance by exploring different feature selection techniques or integrating other machine learning algorithms to improve classification accuracy. Additionally, extending the framework to address other types of misbehavior and incorporating real-time data processing capabilities could enhance its practical utility in real-world VANET environments.

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Method for Predictive Trend Analytics with SNS Information for Marketing

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***Abstract*—A method for predictive trend analytics with social media information is proposed for marketing. Through keyword analysis, page view analysis, access analysis, heat map analysis, Google Analytics, real time analysis, company and competitor analysis, trend analysis with the social media data derived from X (former tweeter), Instagram, Facebook, YouTube, TikTok, market trend can be predicted. The proposed method is created in a local server and is extended to AWS cloud. The proposed system, also ensure negative / positive analysis from the acquired social media information. Through some experiments, it is found that by using AI to analyze social data by category, you can visualize the degree of attention for each keyword, model relationships between information, identify trending keywords, and where the keywords are in their lifecycle. It turns out that it's possible to categorize which ones exist and predict which ones will scale up in the next six months. In addition, corporate product development and marketing personnel can identify themes, materials, benefits, etc. that have signs of becoming popular based on insights based on predictive behavioral data obtained from the proposed method and system and utilize them in new business development and new product planning.**

Keywords*—X (former tweeter); Instagram; Facebook; YouTube; TikTok; market trend; AWS; Google analytics; keyword analysis; page view analysis; access analysis; heat map analysis

I. Introduction

Trend analysis is the process of predicting the future by analyzing changes in certain elements from the past to the present based on information obtained from SNS and websites. Marketing challenges include “difficult to understand cost-effectiveness," “rapid market changes," and “customer needs are diversifying, making it difficult to predict demand." Predict the market and overcome challenges with trend analysis: For example, if you want to know about changes in the market, you can use trend analysis to quickly catch trends in the field of products and services your company provides. Additionally, if it is used when formulating strategies such as production volume and advertising, it is possible to minimize costs.

In order to plan the right marketing measures, it is necessary to accurately understand and analyze all kinds of information. By conducting trend analysis, it is possible to grasp and analyze "information about competitors and market trends" necessary for marketing. In the process of trend analysis, it becomes easy to understand the differences between the products and services offered by your company and those of your competitors, as well as the differences in marketing. By collecting such information, it will be easier to determine the direction your company should take in future business development, and it will also be possible to predict market trends that will lead to the development of new products.

Furthermore, impressions and evaluations of products and services differ between company personnel and consumers. By conducting questionnaire surveys when analyzing trends, you can draw out the true feelings of consumers and formulate more effective marketing strategies. By creating personas using the collected data, you can plan measures that are optimized for users. The more detailed the persona settings are, such as age, gender, occupation, hobbies, and information sources, the better you will understand your customers, and the easier it will be to grasp the needs of actual users. By sharing this data within a company, it is possible to share an image between departments and eliminate misperceptions in marketing.

A method for predictive trend analytics with social media information is proposed for marketing. Through keyword analysis, page view analysis, access analysis, heat map analysis, Google Analytics, real time analysis, company and competitor analysis, trend analysis with the social media data derived from X (former tweeter), Instagram, Facebook, YouTube, TikTok, market trend can be predicted. The proposed method is created in a local server and is extended to AWS cloud. The proposed system, also ensure negative / positive analysis from the acquired social media information.

In the following section, some of the related research works are described in Section II, research background in Section III followed by the proposed method in Section IV. Then, some experiments are described in Section V, followed by a conclusion and future research works in Section VI and Section VII respectively.

II. Related Research Works

Database marketing has been successfully introduced in [1]. The book "Enterprise One to One: Tools for Competing in the Interactive Age" has also been published [2]. An attempt has been made to apply the concept of CLTV (Customer Lifetime Value) to FMCG (Fast-Moving Consumer Goods) [3]. Furthermore, several studies on CLTV have been introduced and reviewed, with each paper presenting different definitions of customer lifetime value, target industries, business models, and conditions for calculation [4].

Instances of COCA (Cost of Customer Acquisition) have been described, which refers to the cost of acquiring customers [5]. CLTV models and applications for marketing have been proposed and their applicability discussed [6]. Marketing study guides have been published and well-reviewed [7].

The book "Customer Profitability and Lifetime Value" has been published and extensively discussed [8]. Managing customers profitably has also been investigated and discussed [9]. Additionally, the analysis and discussion of "Performance management, which includes integrating strategy execution, methodologies, risk, and analytics," has taken place [10].

The paper "RFM (Recent Frequency Monetary) and CLTV: Using iso-value curves for customer base analysis" has been published, proposing and validating a method for marketing research [11]. Similarly, the paper "Autonomous CRM control via CLTV approximation with deep reinforcement learning in discrete and continuous action space" has been published, attempting to use CLTV approximation for CRM control [12].

On the other hand, CLTV has been well defined and discussed [13]. The paper "EDA of predictive modeling with “R” (a software tool for statistics) for risk management using machine learning" has been published, proposing and validating the use of EDA for predictive modeling [14]. Meanwhile, it is widely acknowledged that EDA is an important and useful technique in data science for analyzing and understanding data better. EDA involves exploring and visualizing the data to identify patterns, relationships, and anomalies.

EDA helps identify missing values, outliers, and other inconsistencies in the data, which can then be addressed before building predictive models. By visualizing the data, EDA also facilitates communicating insights to stakeholders and guiding further analysis. Furthermore, EDA is increasingly recognized as a critical step in any data analysis project as it enables a better understanding of the data, identification of potential issues, and provides insights for further analysis and decision-making. The concept of EDA has also been proposed and discussed [15]. Data analysis and regression have been well proposed for EDA analysis [16].

The paper "Suitability of random forest analysis for epidemiological research: Exploring sociodemographic and lifestyle-related risk factors of overweight in a cross-sectional design" has been published, studying and reporting on the suitability of random forest analysis for epidemiological research [17]. Additionally, EDA has been well defined, described, and investigated for its usefulness [18].

The paper "Customer Profiling Method with Big Data based on BDT and Clustering for Sales Prediction" has been published, proposing and validating a method for sales prediction using big data [19]. Meanwhile, the paper "Modified Prophet+Optuna Prediction Method for Sales Estimations" has been published, also proposing and validating a prediction method for sales using actual sales data [20].

III. Research Background

Google Trends is a free tool provided by Google. According to the Ministry of Information and Communications White Paper 2020 Edition, Google will have an 85.6% share of search engines in the world in 2022. By using Google Trends, it can be checked the trend of popular words searched on Google, which has a high share rate in the world, and the rapidly increasing words. For example, it is not only possible to predict demand based on rapidly increasing keywords, but also to understand whether the market is expanding or contracting by checking the increase or decrease in the number of searches for a specified word.

This free tool provided by Yahoo! JAPAN is unique in that it allows you to check X trends in real time. Yahoo! Real-time Search has a feature that allows you to analyze emotions by displaying the ``emotion percentage" in a pie chart, so it can be seen whether the posted content is negative or positive. If opinions about a company's advertising marketing tend toward negative posts, it can be taken improvement actions based on those comments. If it is searched for your company's name or the name of the product or service it offers using X, it can be performed a so-called "ego search" and check the true intentions of a company in real time without any presumptions.

When using SNS for trend analysis, it is important to take advantage of the characteristics of each SNS. In the case of Instagram, a feature is that it analyzes the situations in which trending products and services are used. In the case of X, a feature is that it analyzes what kind of impressions is being expressed about trending products and services. Additionally, in the case of YouTube, a feature is that it analyzes what kind of marketing measures are being taken by other companies.

The usage rate of SNS used by users differs depending on the age group. Only YouTube has a usage rate that accounts for more than half of all age groups, while the usage rate of other SNSs peaks among people in their teens or 20s and then declines. In particular, regarding TikTok, the usage rate among teenagers is 62.4%, while the usage rate among people in their 40s and above has dropped by around 50 points. The number of SNS users is 330 million on X, 1 billion on Instagram, 1 billion on TikTok, 2.934 billion on Facebook, 573 million on Weibo, 193 million on LINE, Pinterest has 444 million people.

The information that can be obtained with PyTrends[1] is things that are gaining attention, interest by subarea, related information, related keywords, and rapidly increasing rankings by year. It provides search suggestions, obtains category content, and investigates up to five keywords at a time for the above items.

TrendScope is a tool that analyzes all of X's past several years of data and articles published in the media, and extracts data that can be used for management decisions, product development, and marketing. It not only captures the current state of the market from the tweets of consumers, but also analyzes past data, making it possible to grasp signs of the future. We can identify which keywords are currently trending, categorize where they are in their lifecycle, and predict which ones will scale up in the next six months. A company's product development and marketing staff can identify themes, materials, benefits, etc. that have signs of becoming a trend, using insights based on predictive behavior data obtained from TrendScope, and utilize this information in new business development and new product planning.

Trends in the world, for example, McDonald's, after the first trend ended, it spread explosively with the second trend. We use AI to catch up on such trends and develop services and

[1] PyTrend：https://norari-kurari-way.com/python-trend/

products that are on-trend. Analyzing the keywords that are rapidly increasing on SNS, knowing the trends at that time, and utilizing them for product development. In addition to product development, by analyzing consumer voices posted on SNS, etc., we can improve existing services. We would like to use this knowledge to improve and create new services that people want. It also collects people's tweets on social media, analyzes the tweets using AI to find trends, and visualizes the analysis results on the screen.

Monitor X posts using Yahoo! Real-time search. It can be checked the number of tweets that include a specific keyword and the actual content of the tweets, and it can be also sorted tweets by newest arrival or topic. In the "emotion ratio" section, posts are automatically judged, and the ratio of positive/negative posts can be displayed. Since we are unable to confirm specific tweets that have been judged positive/negative, we can only confirm these figures as reference numbers. There are tools that can help it finds keywords related to a company that are being talked about and prevent the risk of becoming a hot topic.

IV. Proposed Method

The proposed method allows acquisition of tweet information as an example of SNS information for trend prediction with tweet API in the environment of AWS. The system configuration is shown in Fig. 1.

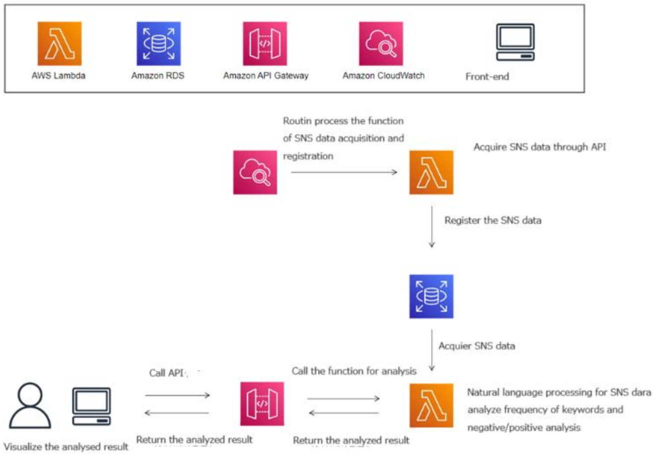

AWS Lambda
Amazon RDS
Amazon API Gateway
Amazon CloudWatch
Front-end
Routin process the function of SNS data acquisition and registration
Acquire SNS data through API
Register the SNS data
Acquier SNS data
Call API
Call the function for analysis
Natural language processing for SNS dara analyze frequency of keywords and negative/positive analysis
Visualize the analysed result
Return the analyzed result
Return the analyzed result

Fig. 1. System configuration of the proposed method for tweet information acquisition relating to trend analysis and prediction based on AWS environment.

There are four major functionalities, AWS Lambda, Amazon RDS, Amazon API gateway, and Amazon CloudWatch together with front end under the user interfaces. As a routine process, the function of SNS data acquisition and registration is always working. With the Lambda, SNS data are acquired through API. Then the acquired SNS data are registered to the Amazon RDS. When users call the API and the function for SNS data analysis, natural language processing is activated. The frequency of keywords is analyzed. Also, after the morphological analysis (part of speech analysis and separation of words) as a part of natural language processing, the acquired SNS data of texts are analyzed with negative or positive of emotional impressions through Lambda. Then the analyzed results are transferred to the users with the front end of visualization terminals.

The database of entities is shown in Table I and Entity Relations are shown in Fig. 2.

TABLE I. Database of Entities

No	Name	Table	Usage
1	User	Customer	Customer Information Control
2	tweet_data	Acquired tweet data	Acquired tweet data control
3	result_data	Tweet analysis result	Tweet analyzed result control
4	category	Category	Category control
5	industry	Industry society	Industry information control

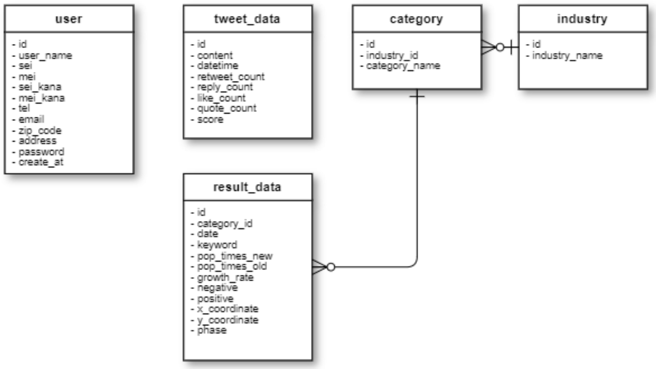


Fig. 2. Entity relations.

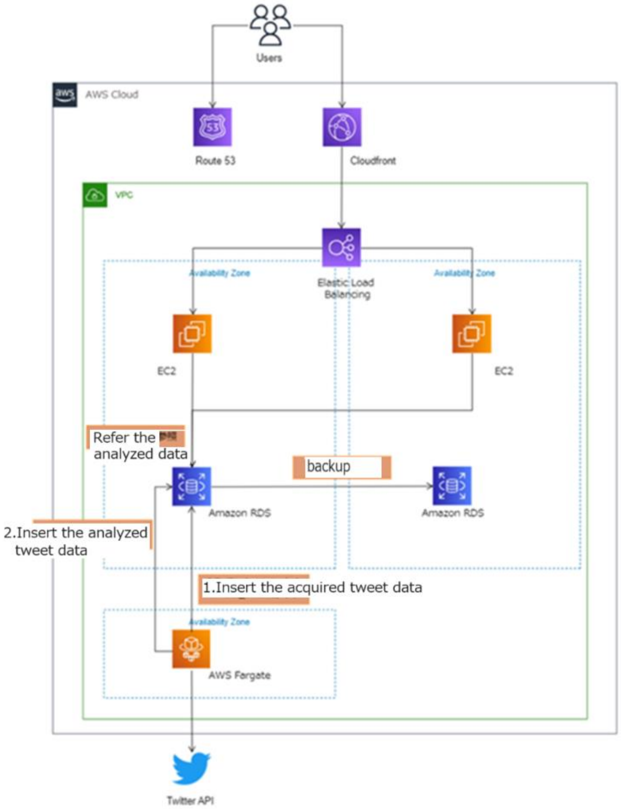


Fig. 3. Detailed configuration of the proposed trend analysis system.

There are five tables in the Amazon RDS, User, Tweet data, Category, Industrial society (Companies in the same industrial society, etc.), and Analyzed result data. The acquired tweet data are categorized based on users, companies. Analyzed results are highly correlated with the categories together with industrial society.

The detailed configuration is shown in Fig. 3. In the figure, backup control scheme and insertion of the acquired SNS data of tweet information as well as referred analyzed results through EC2 are shown. As for the front end, display design of user authentication is shown in Fig. 4. Users have to input their ID and password for authentication and may enter the proposed trend analysis system. After the user authentication, tweet data is collected in accordance with the keywords. Then trend analysis results are appeared together with negative / positive analysis against tweet information of text data. In this stage, “MeaningCloud” of sentiment analysis tool is used as shown in Fig. 5. Thus, the users may realize the impression of tweet information whether or not good or bad. The trend of the users’ impression, then shown in the detailed trend analysis result.

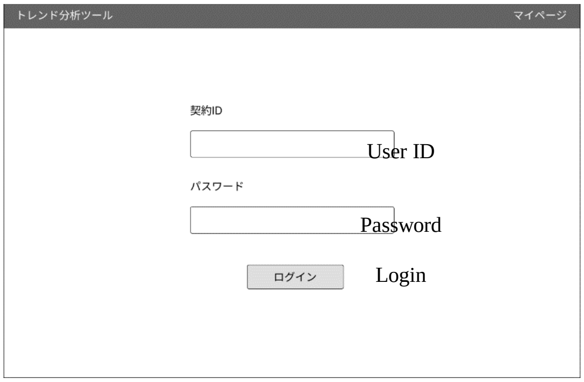
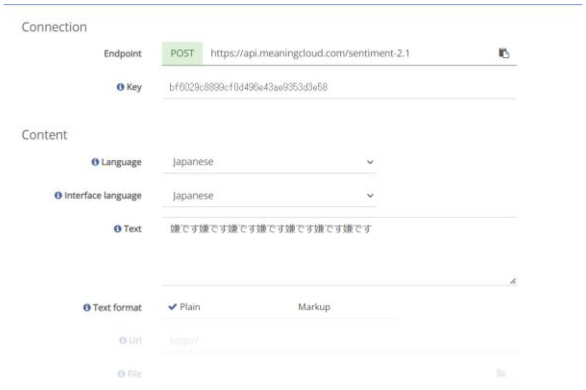


Fig. 4. Login display image.



Endpoint: POST https://api.meaningcloud.com/sentiment-2.1

Key: bf6029c8899cf0d496e43ae9353d3e58

Language: Japanese

Interface language: Japanese

Text: 嫌です嫌です嫌です嫌です嫌です嫌です嫌です

Text format: ✓ Plain Markup

Url: http://

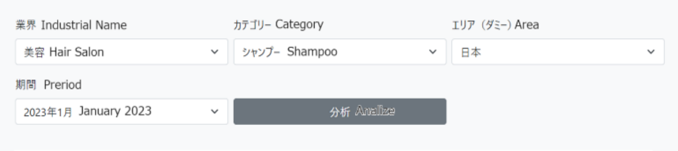
File

Fig. 5. Screenshot of the “meaningcloud”.

V. Experiment

The aforementioned functionalities of the proposed trend analysis system are performed and confirmed. After the user authentication, the main menu appears on the screen as shown in Fig. 6. Pul-down menu is then displayed, “Industry name”, “Category”, “Area”, and “Period” appears. In Fig. 6, “Hair salon”, “Shampoo”, “Japan”, and “January 2023” are selected for each. After all, Analysis of radio button is clicked. Then trend analysis begins.

Fig. 7 shows an example of the detailed trend analysis result with the aforementioned keywords which are shown in Fig. 6.



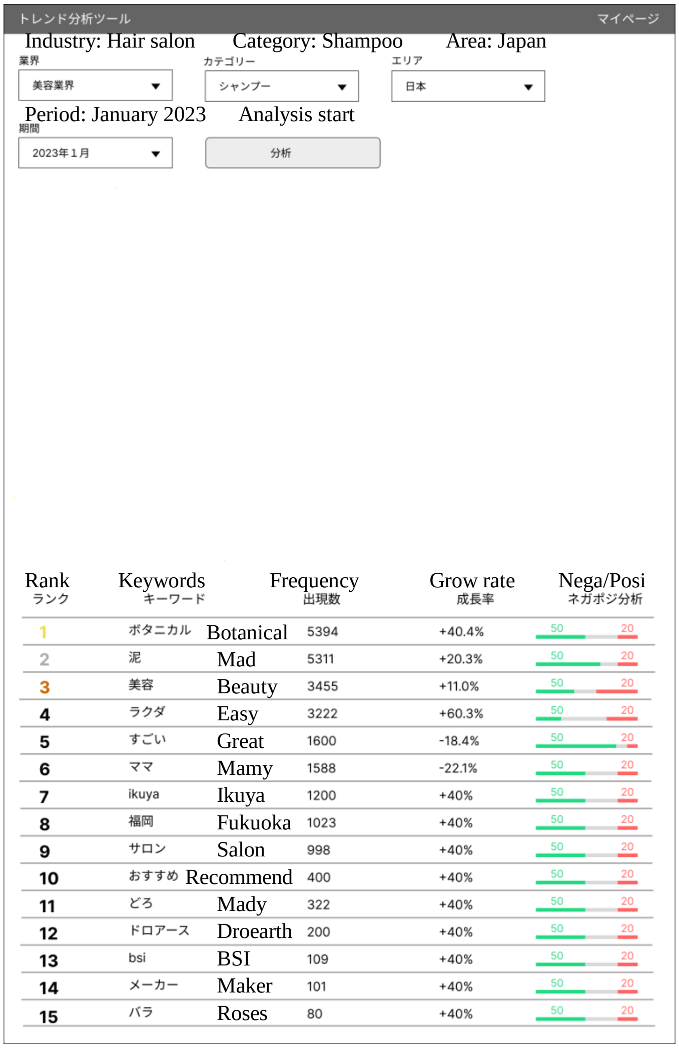
業界 Industrial Name: 美容 Hair Salon

カテゴリー Category: シャンプー Shampoo

エリア（ダミー）Area: 日本

期間 Preriod: 2023年1月 January 2023

Fig. 6. Main menu of the proposed trend analysis system.



Industry: Hair salon 業界: 美容業界

Category: Shampoo カテゴリー: シャンプー

Area: Japan エリア: 日本

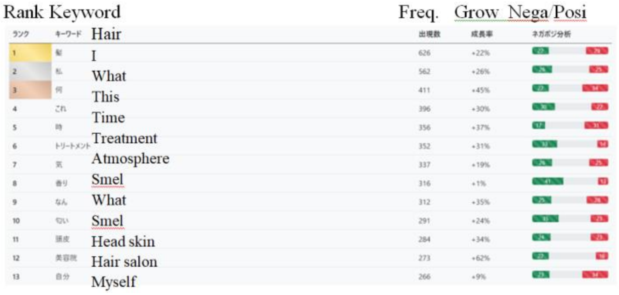
Period: January 2023 期間: 2023年１月

Rank ランク	Keywords キーワード		Frequency 出現数	Grow rate 成長率	Nega/Posi ネガポジ分析
1	ボタニカル	Botanical	5394	+40.4%	50 20
2	泥	Mad	5311	+20.3%	50 20
3	美容	Beauty	3455	+11.0%	50 20
4	ラクダ	Easy	3222	+60.3%	50 20
5	すごい	Great	1600	-18.4%	50 20
6	ママ	Mamy	1588	-22.1%	50 20
7	ikuya	Ikuya	1200	+40%	50 20
8	福岡	Fukuoka	1023	+40%	50 20
9	サロン	Salon	998	+40%	50 20
10	おすすめ	Recommend	400	+40%	50 20
11	どろ	Mady	322	+40%	50 20
12	ドロアース	Droearth	200	+40%	50 20
13	bsi	BSI	109	+40%	50 20
14	メーカー	Maker	101	+40%	50 20
15	バラ	Roses	80	+40%	50 20

Fig. 7. Example of the detailed trend analysis result with the aforementioned keywords.

In January 2023, the top three of the keywords collected from the tweet information with the keyword of “Shampoo” in the hair salon companies in Japan are (1) Botanical, (2) Mad and (3) Beauty. The number of keywords appeared in tweet information for the corresponding top three keywords are 5394, 5311, and 3455. Furthermore, the grow rate of the corresponding keywords is 40.4 %, 20.3 %, and 11.0 %, respectively. Moreover, the sentiment analysis results show almost same ratio of negative and positive impressions of the keywords, 50 % of negative, 30 % of neutral, and 20 % of positive.

Another example is shown in Fig. 8. In January 2023, the top three of the keywords collected from the tweet information with the keyword of “Hair salon” in the hair salon companies in Japan are (1) Hair, (2) I and (3) What. In this case, the extracted keywords are the results from the morphological analysis so that the words are a part of speech. Also, API keys are increased to collect multiple keywords. API option to exclude retweets at the collection stage is added. We delete “Author_id” and delete retweets from existing acquired data. In the meantime, negative / positive analysis is also performed at the time of acquisition for matching with method Positive and Negative dictionary. The number of keywords appeared in tweet information for the corresponding top three keywords are 626, 562, and 411. Furthermore, the grow rate of the corresponding keywords is 22 %, 26 %, and 45 %, respectively. Moreover, the sentiment analysis results show almost same ratio of negative and positive impressions of the keywords, 20 % of negative, 55 % of neutral, and 25 % of positive.

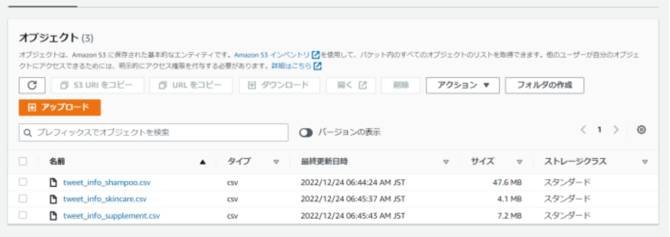


Rank Keyword Freq. Grow Nega/Posi

ランク	キーワード		出現数	成長率	ネガポジ分析	
		Hair				
1	髪	I	626	+22%	22	29
2	私	What	562	+26%	26	25
3	何	This	411	+45%	22	34
4	これ	Time	396	+30%	30	22
5	時	Treatment	356	+37%	17	31
6	トリートメント	Atmosphere	352	+31%	33	14
7	気	Smel	337	+19%	26	25
8	香り	What	316	+1%	41	13
9	なん	Smel	312	+35%	25	28
10	匂い	Head skin	291	+24%	35	23
11	頭皮	Hair salon	284	+34%	24	23
12	美容院	Myself	273	+62%	22	18
13	自分		266	+9%	23	34

Fig. 8. Another example of trend analysis result.

In the experiments, the following keywords, “Shampoo”, “Skin_care”, and “Supplements” are tried. All the collected tweet information with the Tweet API is stored in the csv format in the S3 of Amazone DB as shown in Fig. 9.



オブジェクト (3)

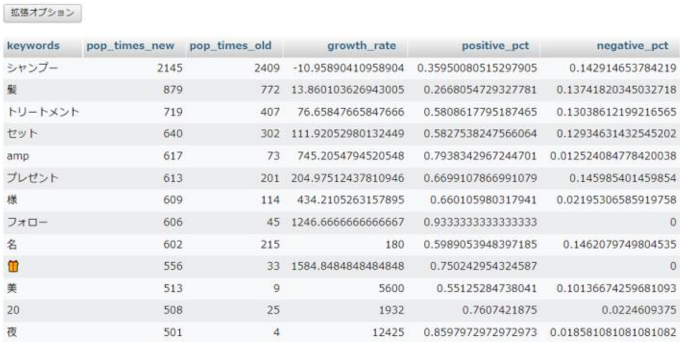
オブジェクトは、Amazon S3 に保存された基本的なエンティティです。Amazon S3 インベントリを使用して、バケット内のすべてのオブジェクトのリストを取得できます。他のユーザーが自分のオブジェクトにアクセスできるためには、明示的にアクセス権限を付与する必要があります。詳細はこちら

	名前	タイプ	最終更新日時	サイズ	ストレージクラス
□	tweet_info_shampoo.csv	csv	2022/12/24 06:44:24 AM JST	47.6 MB	スタンダード
□	tweet_info_skincare.csv	csv	2022/12/24 06:45:37 AM JST	4.1 MB	スタンダード
□	tweet_info_supplement.csv	csv	2022/12/24 06:45:43 AM JST	7.2 MB	スタンダード

Fig. 9. Stored tweet information of data in Amazone S3.

There is the extended option in the Amazone S3. In the option, detailed tweet information of “pop_times_new”, “pop_times_old”, “growth_rate”, “positive_pct”, and “negative_pct” can be displayed as shown in Fig. 10.

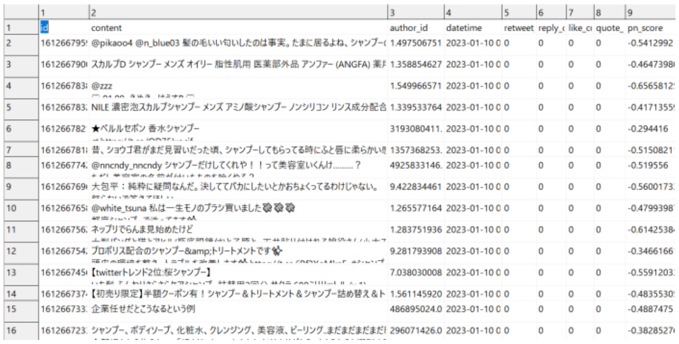
At this time, these tweet information collection, sentiment analysis, and trend analysis run the tweet analysis code using Docker. Similarly, the front end is also implemented on Docker. It was also confirmed that the analysis results were inserted into the Docker DB. When we did this locally, the import took too long, so we had to do it manually, but we changed it to run the tweet analysis method on Docker. At this time, tweets are still being retrieved from S3. Therefore, we made it possible to retrieve it from the DB. Using “FastAPI”, we created an API with Docker to retrieve analysis results from the database. It also allows narrowing down the search by keyword or period.



keywords	pop_times_new	pop_times_old	growth_rate	positive_pct	negative_pct
シャンプー	2145	2409	-10.95890410958904	0.35950080515297905	0.142914653784219
髪	879	772	13.860103626943005	0.2668054729327781	0.13741820345032718
トリートメント	719	407	76.65847665847666	0.5808617795187465	0.13038612199216565
セット	640	302	111.92052980132449	0.5827538247566064	0.12934631432545202
amp	617	73	745.2054794520548	0.7938342967244701	0.012524084778420038
プレゼント	613	201	204.97512437810946	0.6699107866991079	0.145985401459854
様	609	114	434.2105263157895	0.660105980317941	0.02195306585919758
フォロー	606	45	1246.6666666666667	0.9333333333333333	0
名	602	215	180	0.5989053948397185	0.1462079749804535
🎁	556	33	1584.8484848484848	0.750242954324587	0
美	513	9	5600	0.55125284738041	0.10136674259681093
20	508	25	1932	0.7607421875	0.0224609375
夜	501	4	12425	0.8597972972972973	0.018581081081081082

Fig. 10. Example of the extended option display for the acquired tweet information and the negative / positive impressions of sentiment analysis results.

Negative / Positive analysis was also performed when tweets were regularly acquired, and the negative/positive scores were added as an item to the tweet data table as shown in Fig. 11. This is expected to reduce the load during analysis. In the table, tweet ID, Content, author ID, date and time, retweet, and reply, like, quote, positive / negative score are included.



	1	2	3	4	5	6	7	8	9
1	id	content	author_id	datetime	retweet	reply_c	like_c	quote_	pn_score
2	161266795	@pikaoo4 @n_blue03 髪の毛いい匂いしたのは事実。たまに居るよね、シャンプー(	1.497506751	2023-01-10 0	0	0	0	0	-0.5412992
3	161266790	スカルプD シャンプー メンズ オイリー 脂性肌用 医薬部外品 アンファー (ANGFA) 薬	1.358854627	2023-01-10 0	0	0	0	0	-0.4647398
4	161266783	@zzz	1.549966571	2023-01-10 0	0	0	0	0	-0.6565812
5	161266783	NILE 濃密泡スカルプシャンプー メンズ アミノ酸シャンプー ノンシリコン リンス成分配合	1.339533764	2023-01-10 0	0	0	0	0	-0.4171355
6	161266782	★ベルルセボン 香水シャンプー	3193080411.	2023-01-10 0	0	0	0	0	-0.294416
7	161266781	昔、ショウゴ君がまだ見習いだった頃、シャンプーしてもらってる時にふと唇に柔らかい	1357368253.	2023-01-10 0	0	0	0	0	-0.5150821
8	161266774	@nncndy_nncndy シャンプーだけしてくれや！！って美容室いくんけ........？	4925833146.	2023-01-10 0	0	0	0	0	-0.519556
9	161266769	大包平：純粋に疑問なんだ。決してバカにしたいとかおちょくってるわけじゃない。	9.422834461	2023-01-10 0	0	0	0	0	-0.5600173
10	161266765	@white_tsuna 私は一生モノのブラシ買いました😂😂😂	1.265577164	2023-01-10 0	0	0	0	0	-0.4799398
11	161266756	ネップリでらんま見始めたけど	1.283751936	2023-01-10 0	0	0	0	0	-0.6142538
12	161266754	プロポリス配合のシャンプー&amp;トリートメントです✨	9.281793908	2023-01-10 0	0	0	0	0	-0.3466166
13	161266745	【twitterトレンド2位:桜シャンプー】	7.038030008	2023-01-10 0	0	0	0	0	-0.5591203
14	161266737	【初売り限定】半額クーポン有！シャンプー＆トリートメント＆シャンプー詰め替え＆ト	1.561145920	2023-01-10 0	0	0	0	0	-0.4835530
15	161266733	企業任せだとこうなるという例	486895024.0	2023-01-10 0	0	0	0	0	-0.4887475
16	161266723	シャンプー、ボディソープ、化粧水、クレンジング、美容液、ピーリング..まだまだまだま	296071426.0	2023-01-10 0	0	0	0	0	-0.3828527

Fig. 11. The tweet_data table

We also progressed with front-end development. It was able to display graphs and scatter plots. It is also now possible to differentiate plot positions based on phase as shown in Fig. 12.

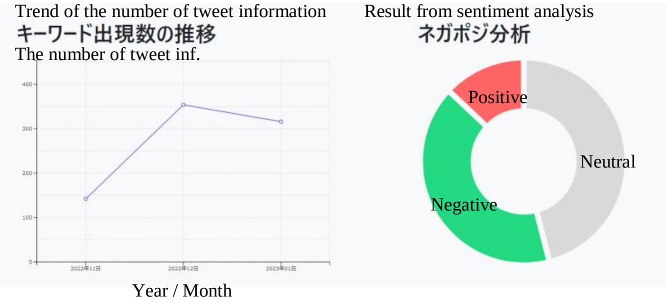
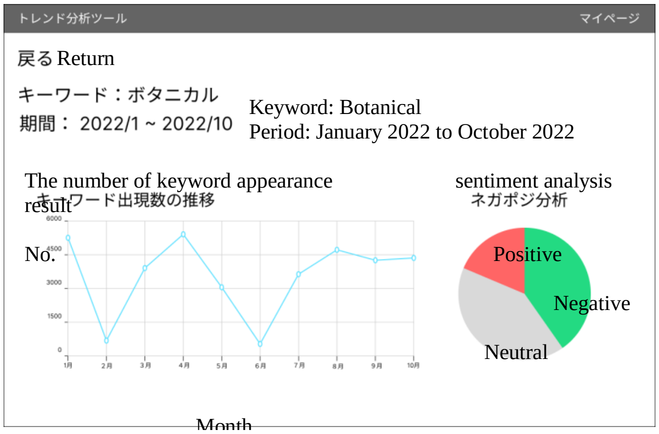


Fig. 12. Example of the Negative / Positive analyzed result.

The example of the final trend analysis result in particular for the number of keywords of “Botanical” and the period during January 2022 and October 2022 as well as Negative / Positive analyzed result is shown in Fig. 13.


戻る Return

キーワード：ボタニカル
期間： 2022/1 ~ 2022/10

Keyword: Botanical
Period: January 2022 to October 2022

Fig. 13. Example of the number of keywords of “Botanical” and the period during January 2022 and October 2022 as well as Negative / Positive analyzed result.

VI. Conclusion

A method for predictive trend analytics with social media information is proposed for marketing. Through keyword analysis, page view analysis, access analysis, heat map analysis, Google Analytics, real time analysis, company and competitor analysis, trend analysis with the social media data derived from X, Instagram, Facebook, YouTube, TikTok, market trend can be predicted. The proposed method is created in a local server and is extended to AWS cloud. The proposed system, also ensure negative / positive analysis from the acquired social media information.

Through some experiments, it is found that by using AI to analyze social data by category, you can visualize the degree of attention for each keyword, model relationships between information, identify trending keywords, and where the keywords are in their lifecycle. It turns out that it's possible to categorize which ones exist and predict which ones will scale up in the next six months. In addition, corporate product development and marketing personnel can identify themes, materials, benefits, etc. that have signs of becoming popular based on insights based on predictive behavioral data obtained from the proposed method and system and utilize them in new business development and new product planning.

VII. Future Research Works

Further investigations are required for not only tweet information derived trend analysis but also Instagram, Facebook, YouTube, TikTok, and so on for market trend has to be predicted in the near future.

Acknowledgment

The authors would like to thank to Professor Dr. Hiroshi Okumura and Professor Dr. Osamu Fukuda for their valuable discussions.

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Study on the Implementation of Multimodal Continuous Authentication in Smartphones: A Systematic Review

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***Abstract*—Profound societal shifts result from the inception of the 4.0 age of the Industrial Revolution and rapid technological advancements. The widespread adoption of e-services has resulted in substantial reliance on smartphones to access diverse offerings. Even so, account breaches and data leaks are risks that users take when they rely so heavily on their smartphones. Authentication is an essential method of safeguarding personal information. The purpose of this study is to undertake a thorough review of the literature on the deployment and trends of multimodal biometric authentication on smartphones. The studies will look at several biometric modalities, such as behavioral and physiological characteristics, and the algorithms for pattern recognition used in continuous authentication systems. The results show various biometric authenticators and emphasize the importance of behavioral features in smartphone authentication. In addition, the research underlines the significance of machine learning algorithms in pattern identification for rapid and accurate analysis. This study helps to understand the present authentication technique landscape and gives ideas for future advances in safe and user-friendly smartphone authentication systems.**

***Keywords*—Authentication; continuous multimodal; biometric authenticator; smartphone**

I. Introduction

The Fourth Industrial Revolution gave birth to significant social disruption, characterized by rapid and highly advanced technological advancements with a particular emphasis on artificial intelligence, big data, and integration systems [1]. This trend encourages every element of society to use electronic service systems in every activity, ranging from the world of business, banking [2], transportation [3], and social organization [4].

In addition, many people use smartphones to access various electronic services via the internet, with 6.4 billion users or 79 percent of the world's total users. The utilization rate of intelligent mobile devices is significantly higher than other devices, such as portable computers and tablets [5].

Internet connection on intelligent mobile devices carries the risk of security vulnerabilities such as account theft and data leakage of its users [6]. Authentication is a meaningful way to keep personal information, such as personal data and more, from falling into the wrong hands [7]. Android devices have used authentication schemes, including pin codes or passwords, patterns, fingerprints, and biometrics [8], where patterns, pins, and alphanumeric passwords are still the preferred way to log into Android devices [9], computers, and web applications such as email, cloud storage, and online shopping services [10], [11].

A knowledge-based authentication, physiological biometrics authentication, behavioral biometrics authentication, and multi-factor authentication are the essential components that comprise the taxonomy of user authentication systems on mobile devices [12]. Regarding security, knowledge-based verification uses information that only people and systems know. The secret can be text, like PINs, codes of letters and numbers, or a picture, like a pattern [12].

Traditional or knowledge-based single-factor authentication has become a significant concern for security practitioners and researchers. While still a viable option due to its simplicity, using PINs, passwords, and patterns as authentication inputs comes with several vulnerabilities, such as surfing and smudge attacks and susceptibility to intercept [13]. Also, password vulnerability causes most users to use passwords that are easy to guess and do not change regularly [14]. The Cybersecurity and Infrastructure Security Agency (CISA) has also added single-factor authentication, such as password matching, to gain access to a system as a bad practice [15].

Other approaches initially anticipated that multi-factor authentication would enhance security [16] and ease ongoing protection for computing devices [17] and other critical services [18] from unauthorized access by using more than two types of credentials [19], such as biometrics and secret knowledge [12]. However, the enhanced security force is still limited. This limitation is supported by other studies that have understood the failure of multi-factor authentication on mobile devices [20]. One flaw in this scheme is that an attacker attempts to intervene in a communication between two interacting parties and modify the message or information transmitted so that the attacker can gain access to confidential data or perform unlawful acts. Furthermore, synchronization issues, hardware alterations, or faults in the implementation of authentication protocols might be used by attackers to gain sensitive information or carry out illicit acts.

Continuous user authentication approaches on smartphones through sensors, multimodal behavioral biometrics, and machine learning models have been introduced in recent research [21], [22], [23] to resolve the previously mentioned issue, improve accuracy, and reduce interference in authentication mechanisms. This method gives a higher level of protection while accessing electronic services via mobile devices, such as smartphones. Previous research in [24] has also conducted systematic reviews of continuous multimodal biometrics but has yet to focus on smartphone implementation. Therefore, this study investigates the possibility of implementing continuous multimodal authentication in mobile devices such as smartphones.

The structure of this paper is as follows. Section II presents the related works. Section III clarifies the concept of multimodal biometrics. Section IV describes the methods used in the study. Section V provide the study's findings and discuss its implications. In Section VI, we present the conclusion and outline future work.

II. Related Work

We discovered limited papers focusing on multimodal continuous authentication in smartphones. Researchers have examined authentication in various ways. For instance, [12] conducted surveys of existing authentication methods on mobile devices, while [13] suggested a behavioral biometric authentication scheme as secure and convenient. Moreover, [17] concluded that biometric authentication alone was insufficient and proposed multi-factor authentication mechanisms for more robust security. The study in [20] explored security vulnerabilities in multi-factor authentication schemes on mobile devices, while [21] identified continuous authentication with behavioral biometrics in smartphones as insightful and challenging for adoption. Furthermore, [23] found that continuous multimodal biometric authentication offers high accuracy and improved security, and [24] suggested implementing and evaluating such systems to demonstrate their feasibility. Based on these studies, we aim to investigate the implementation of multimodal continuous authentication in mobile devices, such as smartphones.

III. Multimodal Biometric

Biometric refers to recognizing patterns that establish a person's identity by comparing biological or behavioral features of biometric attributes. Biometric traits are a highly convenient means of verifying an individual's identity, as they offer high security (difficult to replicate) and cannot be stolen, forgotten, or misplaced [25].

Fingerprints, palm prints, hand geometry, faces, eyes, ears, electrocardiograms, and electroencephalograms are all physiological biometrics used in modern smartphones. Tapping behavior, hand motions, noises, gait, and daily activities are all examples of biometric behavior [12].

A biometric system is, in essence, a pattern recognition system that collects biometric data from a person, extracts a set of features from that data, and then compares the extracted features to a background of templates saved in a database. This process is known as "biometric matching." To put it another way, a pattern recognition system is what a biometric system is. Its performance is determined by the context in which it is used; for example, depending on the context, it may function in either a verification or identification mode [25].

Unimodal and multimodal represent two distinct categories within biometric systems, with their primary distinction lying in the number of modalities employed for authentication purposes. Unimodal biometric systems, exemplified by fingerprint and facial recognition technologies, are easier to create since they only require one identity. However, they are vulnerable to problems like spoofing and poor identification. On the other hand, multimodal systems, such as those combining facial and voice recognition or iris and fingerprint recognition, provide enhanced protection, durability, and adaptability to external influences by employing multiple characteristics. Their intricacy, however, resides in figuring out what, when, and how to combine data for authentication across several modalities [24].

IV. Methodology

The research strategy used for this project was called a Systematic Literature Review (SLR). The SLR technique is a tried-and-true research approach when gathering and analyzing data on a specific issue. We have used the PRISMA guidelines provided by Matthew J. [26]. This SLR consists of four main steps: primary study planning and search, study collection, data extraction, and data synthesis. Section IV(A) identifies research objectives and questions as the first step. In Section IV(B) and IV(C), search strategy steps involve study selection criteria, study selection procedures, keyword formulation for research, and search queries. In Section IV(D), the final step requires quality assessment.

A. Research Question and Objectives

The primary purpose of this SLR is to explore the implementation of continuous multimodal authentication in Smartphones. We create research questions to focus on the objectives of this research.

RQ1: What biometrics is used for authentication on smartphones?

RQ2: What technique is used for pattern recognition in continuous authentication on smartphones?

Based on this research question, the focus of this research objective is to review trends that have occurred in recent years, particularly the use of continuous multimodal authentication on smartphones, and explore biometric combinations used for authentication on smartphones.

B. Search Strategy

In this study, we searched using the electronic databases IEEE Xplore and Scopus. We prepared several lists of keywords to search for relevant literature on multimodal biometric authentication in smartphones from selected electronic databases. The search query utilized was:

“continuous” AND (*biometric* OR *multi*) AND (“authentication” OR “verification” OR “validation”) AND “smartphone” OR “mobile phone.”

Queries applied to article titles, abstracts, and keywords to get relevant articles from electronic databases.

C. Selection Criteria

We analyze the query results that have been obtained by removing duplicate articles. Filtering is also done based on the article’s title, abstract, and keywords. In addition, we also use inclusion and exclusion criteria. Fig. 1 shows the PRISMA diagram for this meta-analysis.

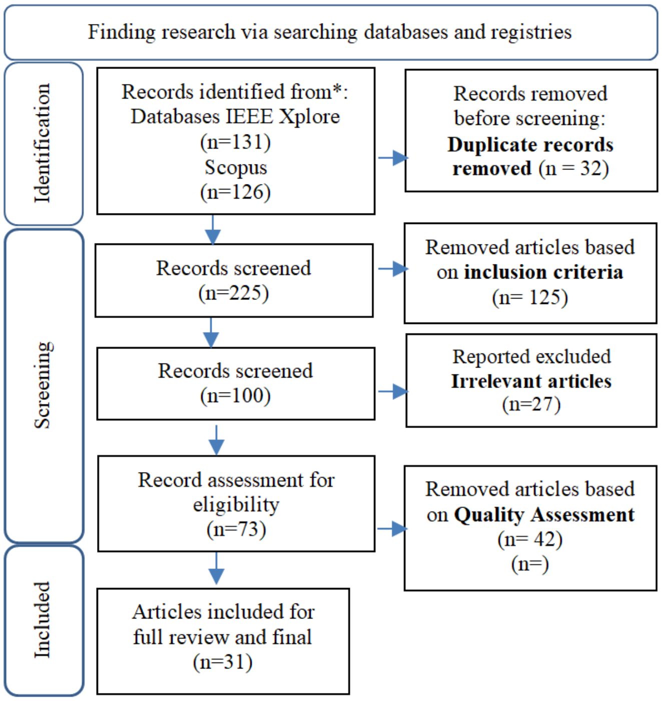
Finding research via searching databases and registries
Identification
Records identified from*: Databases IEEE Xplore (n=131) Scopus (n=126)
Records removed before screening: Duplicate records removed (n = 32)
Screening
Records screened (n=225)
Removed articles based on inclusion criteria (n= 125)
Records screened (n=100)
Reported excluded Irrelevant articles (n=27)
Record assessment for eligibility (n=73)
Removed articles based on Quality Assessment (n= 42) (n=)
Included
Articles included for full review and final (n=31)

Fig. 1. The PRISMA diagram for this meta-analysis.

We use the following inclusion criteria. The paper or article should talk about authentication in smartphones. In addition, papers or articles must be in English and published from 2018 – 2022 in journals or conference proceedings.

We used several article selection exclusion criteria in this study. Papers or articles discuss the continuous multimodal biometric authentication but not in smartphones. In addition, papers or articles in the title, abstract, or keyword section do not mention authentication; articles with survey methods or systematic reviews are not attached to the results of this study.

D. Quality Assessment

Quality assessment is used to assess the quality of the selected article. The quality assessment also evaluates whether the selected article is fully accessible and can answer our review. To determine consistency, we formulated some quality assessment questions.

QA1: Does the article mention the use of continuous multimodal biometric authentication, and is it clearly stated?

QA2: Does the article provide an answer to the formulated RQ?

QA3: Are the aims of the research clearly stated without ambiguity in the paper?

Yes or no can answer each question with weights of 1 and 0, respectively. The results are evaluated after an assessment of the quality of the entire article has been carried out. The quality assessment process is intended for all research articles according to quality assessment questions. Therefore, this review includes all 31 selected articles.

V. Result and Analysis

The study's conclusion will involve presenting research papers that investigate continuous authentication using multimodal methods. Additionally, the second step consists of conducting a mapping exercise to explore the application of biometrics based on specific biometric properties.

A. Significant Journal

In this literature review, 17 journal articles and 14 conference proceedings discuss continuous multimodal authentication. Here is a brief overview of the distribution of publications journals over the past five years. The result is shown in Table I.

Based on Table I, an in-depth analysis of the provided data reveals a diverse collection of journals across different quartiles. Within the esteemed Q1 quartile, we find a constellation of scholarly publications, including Computers & Security, Journal of Network and Computer Applications, IEEE Transactions on Industrial Informatics, IEEE Access, IEEE Internet of Things Journal, Human-centric Computing and Information Sciences, and IEEE Signal Processing Letters. Remarkably, these journals exhibit varying publication frequencies, ranging from 1 to 2, which discuss continuous authentication.

Transitioning to the intellectually stimulating Q2 quartile, we encounter an array of influential journals that contribute significantly to their respective fields. Noteworthy publications such as Electronics Microprocessors and Microsystems, IEEE Transactions on Information Forensics and Security, International Journal of Distributed Sensor Networks, and Sensors grace this quartile, each showcasing their research prowess with a single publication.

TABLE I. Distribution of Publications

Quartile	Journal Name	Quantity
Q3	International Journal of Advanced Computer Science and Applications	1
Q1	Computers & Security	1
Q1	Journal of Network and Computer Applications	2
Q1	IEEE Transactions on Industrial Informatics	1
Q1	IEEE Internet of Things Journal	1
Q2	Electronics	1
Q2	Microprocessors and Microsystems	1
Q1	IEEE Access	2
Q1	Human-centric Computing and Information Sciences	1
Q2	IEEE Transactions on Information Forensics and Security	1
Q2	International Journal of Distributed Sensor Networks	1
Q3	Wireless Communications and Mobile Computing	1
Q4	Indian Journal of Computer Science and Engineering	1
Q2	Sensors	1
Q1	IEEE Signal Processing Letters	1

Intriguingly, the scholarly landscape unveils the distinguished International Journal of Advanced Computer Science and Applications as the sole journal within the intellectually captivating Q3 quartile, signifying its profound impact with a singular publication.

B. Biometric Authenticators

A biometric is a pattern recognition system that establishes a person's identification by comparing biological or behavioral traits of biometric characteristics [26].

Table II presents a captivating exploration of the landscape surrounding biometric authentication within continuous multimodal biometric authentication systems on smartphones, offering a comprehensive overview of the diverse range of biometric authentication methods utilized in intelligent mobile authentication systems that seamlessly integrate multiple biometric modalities sustainably. From this table, we can identify and analyze various biometric authenticators employed in these systems, unveiling a rich tapestry of authentication techniques.

In addition, Fig. 2 illustrates the prevalence of different biometric modalities in authentication systems, revealing that 84% of behavioral characteristics are widely used for smartphone authentication, 13% choose to use physiological factors, and 3% combine behavioral and physiological characteristics. Notably, human gait, routine activities, and touch/swipe functions are emerging as highly preferred options for enhancing the security of continuous authentication processes.

TABLE II. A COMPILATION OF RESEARCH AND BIOMETRIC AUTHENTICATORS USED FOR CONTINUOUS MULTIMODAL AUTHENTICATION

Related Studies	**Behavioral**									**Physiological**			
	Gait	**Gesture**	**Hand Movements**	**Handwriting**	**Keystroke**	**Routine Activities**	**Tapping**	**Touch/ Swipe**	**Mouth Movements**	**Ear**	**Face**	**Eye**	**Palmprint**
[27]								√					
[28]	√												
[29]		√			√								
[30]	√												
[31]							√	√					
[32]													√
[33]	√					√							
[34]											√		
[35]									√				
[36]						√							
[37]	√					√							
[38]					√								
[39]											√		
[40]						√							
[41]									√		√	√	
[42]			√										
[43]			√				√						
[44]								√					
[45]		√											
[46]			√										
[47]	√			√									
[48]										√			
[49]								√					
[50]								√					
[51]			√										
[52]	√												
[53]						√							
[54]			√		√		√						
[55]						√							
[56]					√			√					
[57]								√					

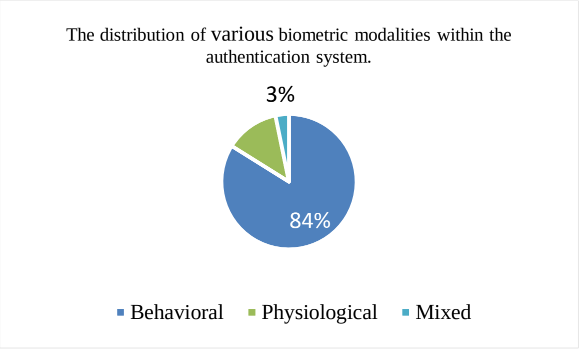

Fig. 2. The proportion of diverse biometric modalities utilized in the authentication system.

An innovative smartphone unlock scheme to improve user authentication through swipe behavior becomes a unique approach where the user selects a background image and performs a swipe action at a specified location on the smartphone screen. This combination ensures secure and reliable authentication, providing an additional layer of protection for smartphone users [27]. Other combinations, such as swipe and tap, result in increased security through continuous user authentication by paying attention to factors such as vibrations from walking, the effects of different positions, and trembling hands in cold temperatures [31] and the number of tap gestures implemented without any combination [49], [50], [57].

The continuous implementation of authentication and identification security is also demonstrated using behavioral characteristics in everyday life. Activities of daily living, such as walking, typing, and clapping, can be used for authentication and biometric identification. This demonstrates the feasibility of using natural activities for continuous biometrics with the help of smartphone motion sensors and inertial measurement datasets [53], [55]. Another approach through an innovative scheme also offers a dynamic and personalized user validation process by analyzing six everyday activities: walking, running, standing, sitting, walking up, and walking down. The variety of positions for smartphone placement on the user's body affects the user's recognition of each specific activity. This can optimize sensor placement and improve the overall performance of recognition systems [40].

The development of human gait recognition for smartphone access shows the advantages of biometric authentication methods to enhance security and prevent illegal user access [28]. The system's hidden nature, which does not require user interaction, further confirms its advantages as a convenient and user-friendly layer of security [30]. By utilizing smartphones' built-in inertial sensors, data collection can be done smoothly without burdening the user, making it a highly efficient, scalable, and robust modality for smartphone user authentication [33], [52].

Another approach in the realm of physiological characteristics, using the front-facing camera on devices, enables capturing the user's facial features and facial attributes (e.g., eyes) [39], [41]. Current face authentication approaches train the system using facial data from a single context or several contexts with no separation. However, camera exposure recognition is essential to improve facial recognition performance in different circumstances. The contingency for elevated accuracy thresholds arises when illumination conditions play a pivotal role in facial image recognition, owing to their substantial impact [39].

MetaEar is a cutting-edge method of modeling and authenticating Ear-Related Transfer Function (ERTF) biometrics from the human ear using Frequency-Modulated Continuous Wave (FMCW) ultrasonics. The system uses FMCW ultrasonic waves and twin microphones to record and analyze the feedback sound wave for extracting ERTF characteristics [48].

C. Pattern Recognition Techniques

Pattern recognition techniques play an essential role in smartphone continuous biometric authentication systems, enabling the automatic identification and classification of patterns in data for efficient and accurate analysis. Recent advances in machine learning algorithms have revolutionized pattern recognition, offering powerful tools for extracting meaningful information from complex data sets. Fig. 3 depicts utilization patterns of classification techniques in continuous multimodal biometric authentication systems based on an SLR.

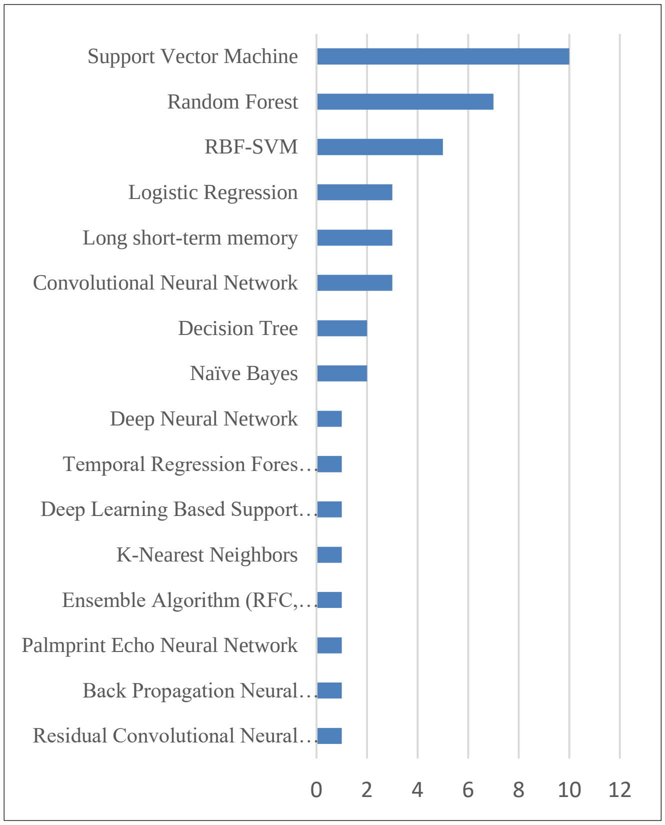

Fig. 3. The utilization patterns of classification techniques in continuous multimodal biometric authentication systems.

The study conducted by Benegui used four different Convolutional Neural Network (CNN) architectures with varying depths as embedding extractors [30]. These networks have a similar structure, using SoftMax activation at the classification layer and Rectified Linear Units (ReLU) at another layer. Experimental results demonstrate the outstanding suitability of the gait-based dataset for the task at hand, enabling the passive collection of gait data and continuous user identification, serving as a robust continuous authentication mechanism.

In addition, CNN shows superior performance compared to traditional machine learning classifiers such as Support Vector Machine (SVM), k-nearest Neighbors, Random Forest, and Linear Discriminant Analysis (LDA) when applied to behavioral characteristics based on routine activities [33]. The inherent time-invariant nature of CNN makes it particularly suitable for processing time series data in behavioral biometrics, such as the analysis of hand movements [42].

The Long Short-Term Memory (LSTM) model undergoes an optimization process to determine the optimal set of parameters for a particular task. Compared to CNN and ConvLSTM architectures, six-layer CNN outperforms ConvLSTM in terms of accuracy and generalization [30]. An LSTM-based architecture is used in the authentication model to capture user behavior patterns while holding their smartphone, regardless of activity. As shown through keystroke dynamics analysis, LSTM classifiers show promising potential in predicting user behavior, even with limited data availability [54].

Unsupervised user verification demonstrates remarkable performance with minimal training time. The authentication system effectively handles various activities and routines using a dedicated single-class SVM model, resulting in exceptional accuracy [37]. Moreover, SVM classifiers are trained on facial characteristics using advanced methods like face warping and textual feature extraction, ensuring precise face identification [41]. The authentication process further incorporates the analysis of touchscreen interactions and subtle micro-gestures, enhancing the overall accuracy and reliability of the system [31].

In other techniques, Random Forest (RF) is often used for prediction and classification because the computational complexity is relatively low, and the training is faster [50]. RF technique is also utilized to identify motion status, touch gesture characteristics, keyboard patterns, and short-term activities. [29], [45], [50]. The pattern recognition field also extensively uses another statistical method called logistic regression. On the other hand, the author favors this option due to its simplicity and dependability and the fact that it is included in the Weka library [29], [39].

D. Discussion

We discovered 13 biometric authenticators that use behavioral and physiological aspects for authentication. Behavioral factors are used most frequently for smartphone authentication, followed by physiological and mixed techniques. In addition, we identified 16 pattern recognition approaches critical for constructing a continuous multimodal biometric authentication system. Fig. 3 depicts the ranked pattern recognition techniques that were used.

Based on these findings, it can be concluded that behavioral traits have been widely implemented in smartphone authentication. The combination of biometric authentication ensures secure and reliable authentication, providing an additional layer of protection for smartphone users. Furthermore, selecting pattern recognition techniques is crucial in continuous biometric authentication systems on smartphones. This ensures the automatic identification and classification of data patterns for efficient and precise analysis.

VI. Conclusion and Future Works

A. Conclusion

The SLR method was employed in this study to investigate the implementation of continuous multimodal authentication in Smartphones. The study's findings revealed a diverse collection of journals across different quartiles, with notable publications discussing continuous authentication in Q1 and Q2 journals. The examination of biometric authenticators revealed a diverse set of methodologies, with behavioral traits being the most often utilized for smartphone authentication. Behavioral variables, such as human movement and customary activities, are used for smartphone authentication, followed by physiological characteristics and a mix of both.

Additionally, the research emphasized the popularity of pattern recognition algorithms, including neural networks based on convolution and long-term and short-term memory models. These showed more extraordinary performance when evaluating behavioral biometrics. Support Vector Machine, Random Forest, and Logistic Regression were also used for classification and prediction. Overall, the study provided insights into the landscape of biometric authentication and pattern recognition techniques in continuous multimodal biometric authentication systems on smartphones.

This research contributes to understanding the implementation of continuous multimodal authentication on smartphones. The findings highlight the importance of behavioral characteristics and the effectiveness of pattern recognition techniques in enhancing security and user authentication. The diverse range of journals and the prevalence of advanced machine-learning algorithms in the field demonstrate significant advancements in this area of research. Future studies can further explore the performance and usability of these authentication methods and investigate new approaches to enhance continuous authentication on smartphones.

B. Limitations and Future Works

The research had certain limitations. Initially, it concentrated primarily on multimodal continuous authentication in smartphones. Second, it only looked at multimodal biometrics, not unimodal biometrics. Future studies could investigate a broader range of devices that require authentication techniques. Furthermore, additional research might focus on unimodal biometrics or compare unimodal and multimodal biometrics across different devices.

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Elevating Student Performance Prediction using Extra-Trees Classifier and Meta-Heuristic Optimization Algorithms

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Abstract—**In the highly competitive landscape of academia, the study addresses the multifaceted challenge of analyzing voluminous and diverse educational datasets through the application of machine learning, specifically emphasizing dimensionality reduction techniques. This sophisticated approach facilitates educators in making data-informed decisions, providing timely guidance for targeted academic improvement, and enhancing the overall educational experience by stratifying individuals based on their innate aptitudes and mitigating failure rates. To fortify predictive capabilities, the study employs the robust Extra-Trees Classifier (ETC) model for classification tasks. This model is enhanced by integrating the Gorilla Troops Optimizer (GTO) and Reptile Search Algorithm (RSA), cutting-edge optimization algorithms designed to refine decision-making processes and improve predictive precision. This strategic amalgamation underscores the research's commitment to leveraging advanced machine learning and bio-inspired algorithms to achieve more accurate and resilient student performance predictions in the mathematics course, ultimately aiming to elevate educational outcomes. Analyses of G1 and G3 showcase the efficacy of the ETRS model, demonstrating 97.5% Accuracy, F1-Score, and Recall in predicting the G1 values. Similarly, the ETRS model emerges as the premier predictor for G3, attaining 95.3% Accuracy, Recall, and F1-Score, respectively. These outcomes underscore the significant contributions of the proposed models in advancing precision and discernment in student performance prediction, aligning with the overarching goal of refining educational outcomes.**

Keywords—Student performance; mathematics; machine learning; Extra-Trees Classifier; Gorilla Troops Optimizer; Reptile Search Algorithm

I. Introduction

A. Background

The achievement of academic success by students is a core aim in education and a crucial component of any country's educational agenda. Emphasizing the significance of quality education as a driver for societal transformation, educational institutions are compelled to give priority to the development of students who excel not only in academic and non-academic evaluations but also acquire vital practical skills to remain competitive in the job market. Education, central to societal progress, reflects the shared aspirations for well-being and advancement [1]. The emphasis on the caliber of students graduating from schools has emerged as a significant worry. As underscored by Spinath [2], [3], academic success occupies a central position, serving as a gauge for intellectual education and an essential requirement for personal and societal well-being. In this context, Martín asserts that academic achievement goes beyond intellectual quotient (IQ), encompassing diverse dimensions to encompass the cognitive, psychomotor, and affective aspects of students' development [4], [5], [6].

The main advantage of data mining is its capability to meticulously analyze large datasets and formulate rules that can attract the interest of pertinent stakeholders. Additionally, it has the potential to unveil previously unknown and valuable insights that significantly enhance decision-making. Machine learning (ML) algorithms, particularly noted for their efficacy in classification tasks, stand as a focal point in various research pursuits [7], [8], [9]. As per the findings of Sharma, Himani, and Kumar [10], decision tree algorithms are widely acknowledged as effective tools for classification purposes. Decision trees, which are structured models comprising root nodes, branches, and leaf nodes, serves the functions of predicting outcomes. These trees exhibit versatility in handling both numerical and categorical data, are easily comprehensible, and can be visually represented. Their pivotal role extends to the identification of group characteristics, exploration of relationships between variables, and application in predicting various educational outcomes, including student performance. Jorda and Raqueno [11] underscore the significance of diverse decision tree algorithms such as C&R Tree, CHAID, C 5.0, and QUEST, emphasizing their role in the development of classification systems [12], [13], [14].

B. Related Works

Many scholars have conducted thorough investigations into the diverse factors that impact student success across different academic levels [15], [16], [17], [18]. Numerous studies in this realm have employed data mining techniques, specifically classification algorithms, to improve the overall quality of higher education systems and to forecast student performance. This section highlights a selection of pertinent studies; particularly those centered on the utilization of decision trees and classification methods in assessing students' academic performance [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29].

As an illustration, Al-Radaideh et al. [30] conducted a study proposing a decision tree classification model aimed at assisting school management in selecting appropriate academic tracks for students, thereby streamlining decision-making processes. Thammasiri et al. [31] introduced a model designed to predict inadequate academic performance among freshmen. By combining support vector machines with SMOTE (Synthetic Minority Over-sampling Technique), they achieved an impressive accuracy rate of 90.24%, effectively addressing class imbalance issues. Mustafa et al. [32] utilized the CRISP framework to assess students' data in C++ courses, conducting a comparative analysis of classifiers such as ID3, C4.5 decision trees, and Naive Bayes. The C4.5 decision tree exhibited superior performance, offering insights into the attributes influencing student performance. Nguyen and Peter [33] investigated the efficacy of decision trees and Bayesian networks in forecasting the academic performance of undergraduate and postgraduate students, with their findings indicating the superior performance of decision trees. Sunita and LOBO L.M.R.J [34] showcased the practicality of data mining in the realm of education by employing classification and clustering algorithms to predict student performance and group students accordingly. Bichkar and R. R. Kabra [35] developed classification models geared towards identifying at-risk students among first-year engineering students. Bharadwaj and Pal [36] applied the ID3 decision tree algorithm to predict student divisions based on various academic indicators. Edin Osmanbegovic et al. [37] formulated a model aimed at predicting student academic success, specifically addressing challenges related to data dimensionality. Despite Naïve Bayes achieving the highest accuracy at 76.65%, the model fell short in effectively handling the class imbalance issue. Surjeet and Pal [38] utilized various decision tree algorithms to forecast the performance of first-year engineering students, focusing on the identification of those at risk of failure. Mahfuza and Shovon [13] proposed a hybrid approach that combines clustering and classification to categorize students into high, medium, and low standards, enabling informed decisions about their academic performance and ultimately enhancing their final examination results. Kabakchieva [39] compared data mining algorithms for predicting student performance and classifying students as strong or weak, with the neural network achieving high accuracy for the strong class. Carlos et al. [40] employed machine learning to create a model for predicting student failure, achieving a notable accuracy of 92.7% with the ICRM classifier. The summary of several related studies was reported in Table I.

TABLE I. LITERATURE REVIEW

No.	Author (s)	Models	Accuracy	Reference
1	Al-Radaideh et al.	DTC	87.9%	[30]
2	Nguyen and Peter	DTC	82%	[33]
3	Bichkar and R. R. Kabra	DTC	69.94%	[35]
4	Edin Osmanbegovic et al.	NBC	76.65%	[37]
5	Carlos et al. [40]	ADTree	97.3%	[40]
6	Kabakchieva	DTC	72.74%	[39]

C. Objective

Employing the Extra-Trees Classifier (ETC) technique, this research had the primary objective of developing a robust Machine learning model for predicting student performance, leveraging data from reliable sources. In creating these models, the study introduced an innovative approach by seamlessly integrating two optimization algorithms: the Gorilla Troops Optimizer (GTO) and the Reptile Search Algorithm (RSA). The decision to integrate these optimization algorithms stems from their complementary strengths. GTO, inspired by gorilla troop foraging behavior, balances global and local search strategies, while RSA adapts to changing environments efficiently. This novel combination of techniques aimed to enhance the accuracy and precision of the predictive model, ultimately contributing to more effective student performance forecasts in an educational context. The ETC model is employed in predicting and classifying student performance due to its robustness and effectiveness. ETC minimizes overfitting, enhances accuracy, and handles diverse data patterns. This model is particularly valuable in educational contexts where the prediction of student outcomes requires a versatile and resilient algorithm capable of capturing nuanced relationships within complex datasets. Subsequently, in Section II, the material and methodology of the research are prepared; Section III contains information about the evaluation methods, results, and discussion of prediction models; and finally, the results of classification models. In the end, Section IV concludes the important findings of the study.

II. MATERIALS AND METHODOLOGY

A. Extra-Trees Classifier (ETC)

Geurts et al. [41] introduced the Extra Trees Classifier as a modification of the Random Forest algorithm. This model, acknowledged as a highly randomized tree classifier or redundant tree classifier, operates through the utilization of an ensemble learning approach. The Extra-Trees algorithm constructs an ensemble of decision or regression trees via the conventional top-down procedure. Its primary distinctions from other tree-based ensemble methods lie in two key aspects: firstly, it randomly selects cut-points for node splits, and secondly, it employs the entire learning sample for the growth of the trees.

The Extra-Trees algorithm employs a randomized splitting procedure for numerical attributes, controlled by parameters K (number of randomly selected attributes at each node) and n_{min} (minimum sample size for node splitting). The method utilizes the full original learning sample multiple times to create an ensemble model with M trees. Predictions are aggregated through majority vote or arithmetic average for classification and regression, respectively. The approach aims to reduce variance by explicit randomization of cut points and attributes, outperforming other methods. Using the full learning sample minimizes bias. Despite a complexity of $N \log N$, the simplicity of the node-splitting procedure contributes to computational efficiency. Parameters K, n_{min}, and M influence attribute selection, noise averaging, and variance reduction, respectively. While adaptable, default settings are preferred for computational advantages and method autonomy.

The process of dividing attributes in Extra-Trees is outlined as follows:

```
Split a node (S)
Input: for the node designated for splitting, present the local learning subset $S$. The resulting output is either a split, denoted as [$a < a_c$], or no result.
– If Stop split(S) is TRUE then return nothing.
– Otherwise select $K$ attributes {$a_1, . . ., a_k$} among all non-constant (in $S$) candidate attributes;
– Draw $K$ splits {$s_1, . . ., s_k$}, where $s_i$= Pick a random split ($S$,$a_i$ ), $\forall_i$= 1, . . ., K;
– Return a split $s_*$ such that Score ($s_*$, S) = maxi=1..., $K$ Score ($s_i$, S)
Pick a random split ($\boldsymbol{S}$,a)
Inputs: a subset $S$ and an attribute $a$
Output: a split
– Let $a^s_{max}$ and $a^s_{min}$ denote the maximal and minimal value of $a$ in $S$;
– Draw a random cut-point $a_c$ uniformly in [$a^s_{max}$, $a^s_{min}$ ];
– Return the split [a < $a_c$].
Stop split ($\boldsymbol{S}$)
Input: a subset $S$
Output: a Boolean
– If |S| < $n_{min}$, then return TRUE;
– If all attributes are constant in $S$, then return TRUE;
– If the output is constant in $S$, then return TRUE;
– Otherwise, return FALSE.
```

B. *Gorilla Troops Optimizer (GTO)*

The genesis of the GTO technique can be traced back to the observation and analysis of social intelligence within gorilla groups in their natural habitats [42]. In this methodology, every gorilla is considered a potential solution, and the optimal solution at each optimization stage is identified as the silverback gorilla. The optimization process is delineated into two key phases: exploration and exploitation. To stimulate exploration, three strategies are implemented, with one of them entailing the migration of gorillas to unexplored areas. The objective of this migration strategy is to augment the exploration process, as elucidated in Eq. (1).

$$GX(t+1) = (UL - LL) \times r_1 + LL, Rnd < O \tag{1}$$

The second approach entails transitioning to a different gorilla group, contributing to the equilibrium between exploration and exploitation, as articulated in Eq. (2).

$$GX(t+1) = (r_2 - C) \times X_r(t) + L \times H, Rnd \geq 0.5 \tag{2}$$

The third tactic involves relocating to the designated site, primarily focused on augmenting the GTO's capacity to explore varied optimization spaces, as elucidated in Eq. (3).

$$GX(t+1) = X(i) - L \times \Big(L \times \big(X(t) - GX_r(t)\big) + r_3 \times \big(X(t) - GX_r(t)\big)\Big), Rnd < 0.5 \tag{3}$$

where, $GX(t+1)$ signifies the potential solution position of a gorilla in the subsequent iteration, while $X(t)$ is the current position vector of the gorilla. Rnd, r_1, r_2, and r_3 are random values in the range of $[0-1]$. The parameter o denotes the probability of opting for the migration strategy to an unfamiliar position and must be predetermined between 0 and 1 prior to initiating the optimization process. X_r represents a randomly chosen member from the gorilla group, while GX_r denotes the potential solution vector position of the gorilla, chosen at random. LL and UL represent the lower and upper limits of the variables, respectively. Additionally, C, L, and H can be defined through mathematical expressions as per Eq. (4) to Eq. (6).

$$C = (\cos(2 \times r_4) + 1) \times (1 - t/\max(t)) \tag{4}$$

$$L = C \times l \tag{5}$$

$$H = Z \times X(t) \tag{6}$$

Here, r_4 signifies a random value within the range of 0 to 1, while l represents a random value within the range of -1 to 1, and Z denotes a random value that ranges from $-C$ to C. If the value of $Rand$ is below p, the first strategy is executed. Conversely, if $Rand$ is greater than or equal to 0.5, the second strategy is applied, and if $Rand$ is less than 0.5, the third strategy is chosen. The optimal solution acquired during the exploration phase is subsequently identified as the silverback.

To enhance exploitation, the GTO methodology incorporates two strategies. The initial strategy entails tracking the silverback, which is the designated gorilla, symbolizing the optimal solution. This strategy is activated when the value of the parameter C exceeds the random parameter W. The silverback assumes the role of a leader guiding other gorillas in foraging for food. This behavior can be expressed mathematically through Eq. (7) and Eq. (8), where, $g = 2^L$.

$$GX(t+1) = L \times M \times (X(t) - X_{sb}) + X(t) \tag{7}$$

$$M = \left(\left|\left(\frac{1}{n}\right)\sum_{i=1}^{n} GX_i(t)\right|^g\right)^{1/g} \tag{8}$$

Here, X_{sb} signifies silverback gorilla.

The alternate exploitation strategy centers around vying for the adult female gorilla. This course is selected when the value of the parameter C falls below the random parameter W. In their native environment, young male gorillas engage in intense competition to win the favor of a female gorilla. This conduct can be mathematically articulated through Eq. (9).

$$GX(t+1) = X_{sb} - (X_{sb} \times Q - X(t) \times Q) \times V \tag{9}$$

$$Q = 2 \times r_5 - 1 \tag{10}$$

$$V = \gamma \times I \tag{11}$$

Here, Q signifies the force of impact, with r_5 representing a random value within the range of $[0-1]$. V is a vector signifying the intensity of aggression during a conflict, and γ is a predetermined value established before initiating the optimization process. I denotes the influence of aggression on the solution's dimensions. The optimal solution derived from the exploitation phase is then assigned the role of the new silverback. This designation could either be retained from the chosen gorilla during the exploration phase or newly selected.

The pseudo-code of GTO is provided below [43]:

Algorithm 1. The pseudo-code of GTO.

```
GTO setting
Inputs: The population size $n$ and maximum number of iterations $T$ and parameters $\gamma$ and $O$
Outputs: The location of the Gorilla and its fitness value
Initialization
Initialize the random population $X_i (i = 1,2,\dots,n)$
Calculate the fitness values of the Gorilla
Main Loop
while (stopping condition is not met) do
    Update the $C$
    Update the $L$
    Exploration phase
    for (each Gorilla ($X_i$)) do
        Update the location of Gorilla
    end for
    % Create group
    Calculate the fitness values of the Gorilla
    if $GX$ is better than $X$, replace them
    Set $X_{sb}$ as the location of $silverback$ (best location)
    % Exploitation phase
    for (each Gorilla ($X_i$)) do
        if ($|C| \geq 1$) then
            Update the location of Gorilla
        else
            Update the location of Gorilla
        end if
    end for
    % Create group
    Calculate the fitness values of the Gorilla
    if New Solutions are better than previous solutions, replace them
    Set $X_{sb}$ as the location of $silverback$ (best location)
end while
Return $X_{BestGorilla}$, $bestFitness$
```

C. Reptile Search Algorithm

The Reptile Search Algorithm (RSA) draws inspiration from the foraging behaviors observed in crocodiles within their natural environment [44]. It operates by alternating between encircling and hunting search phases, with the transition between these phases achieved by dividing the total number of iterations into four segments [45], [46].

1) Initialization phase: *The Reptile Search Algorithm commences by stochastically generating an initial set of solution candidates using the following equation:*

$$X_{ij} = rnd \times (UB - LB) + LB \quad j = 1,2,\dots,n \tag{12}$$

In the initialization matrix (X_{ij}) mentioned earlier, the variable j corresponds to the population size, indicating the number of rows in the matrix. LB and UB denote the lower and upper bound constraints, respectively, and rnd signifies randomly generated values employed in the initialization process.

2) Exploration (Encircling phase): The encircling phase primarily involves navigating an area with a high density of potential solutions. In this phase, movements inspired by crocodile behaviors, such as high walking and belly walking, plays a crucial role. It is essential to emphasize that these movements are not directly focused on capturing prey; instead, their purpose is to explore a wide search space within the optimization process.

$$X_{ij}(\vartheta + 1) = OPT_j(\vartheta) \times \left(-\rho_{(ij)}(\vartheta)\right) \times \varepsilon - \left(R_{ij}(\vartheta) \times rnd\right), \quad \vartheta \leq \frac{N}{4} \tag{13}$$

$$X_{ij}(\vartheta + 1) = OPT_j(\vartheta) \times X_{(r_1,j)} \times ES(\vartheta) \times rnd, \vartheta \leq \frac{2N}{4} and\ \vartheta > \frac{N}{4} \tag{14}$$

Here, $OPT_j(\vartheta)$ represents the optimal solution obtained at the jth position, where ϑ denotes the current iteration number, and N is the maximum number of iterations. $\rho_{(ij)}$ represents the value generated by the hunting operator for the ith solution at the jth position. The parameter ε explains the sensitivity, influencing the exploration accuracy. R_{ij} is utilized to reduce the search space area. The calculations for $\rho_{(ij)}$ and R_{ij} are as follows:

$$\rho_{(ij)} = OPT_j(\vartheta) \times P_{(i,j)} \tag{15}$$

$$\rho_{(ij)} = \frac{OPT_j(\vartheta) - P_{(r_2,j)}}{OPT_j(\vartheta) + \alpha} \tag{16}$$

Here, the variable r_1 is a randomly generated number within the range of $[1 - T]$, where T represents the total count of candidate solutions. $X_{(r_1,j)}$ signifies a randomly chosen position for the jth solution. Similarly, r_2 is another randomly generated number ranging from $[1 - T]$, and α denotes a small-magnitude value. $ES(\vartheta)$ denoted as Evolutionary Sense, is a probability-based ratio. The mathematical expression of Evolutionary Sense can be articulated as follows:

$$ES(\vartheta) = 2 \times r_3 \times \left(1 - \frac{1}{N}\right) \tag{17}$$

In this scenario, the variable r_3 represents a randomly generated numerical value. The calculation of $P_{(i,j)}$ is determined using the following formula:

$$P_{(i,j)} = \varepsilon + \frac{X_{(i,j)} - A(X_i)}{OPT_j(\vartheta) \times (UB - LB) + \alpha} \tag{18}$$

$$AVG(X_i) = \frac{1}{T} \sum_{j=1}^{T} X_{(i,j)} \tag{19}$$

where, $AVG(X_i)$ represents the average position of the ith solution.

3) Exploitation (Hunting phase): The hunting phase involves two key strategies: hunting coordination and cooperation. These strategies play a crucial role in local-scale exploration, resembling the pursuit of optimal solutions, similar to hunting prey. The hunting phase is segmented based on the current iteration number. The hunting coordination strategy operates when the iteration number ϑ is within $\vartheta \leq \frac{3N}{4}$ and $\vartheta > \frac{2N}{4}$, while the hunting cooperation strategy is applied when $\vartheta \leq N$ and $\vartheta > \frac{3N}{4}$. These strategies incorporate stochastic coefficients to explore the local search space and generate optimal solutions systematically. The exploitation phase is guided by Eq. (9) and Eq. (10) to facilitate this process.

$$X_{ij}(\vartheta + 1) = OPT_j(\vartheta) \times P_{ij}(\vartheta) \times rnd,$$

$$\vartheta \leq \frac{3N}{4} \ and \ \vartheta > \frac{2N}{4} \tag{20}$$

$$X_{ij}(\vartheta + 1) = OPT_j(\vartheta) - \rho_{(ij)}(\vartheta) \times \alpha - R_{ij}(\vartheta) \times rnd, \vartheta \leq Nand \ \vartheta > \frac{3N}{4} \tag{21}$$

The RSA process is illustrated in Fig. 1.

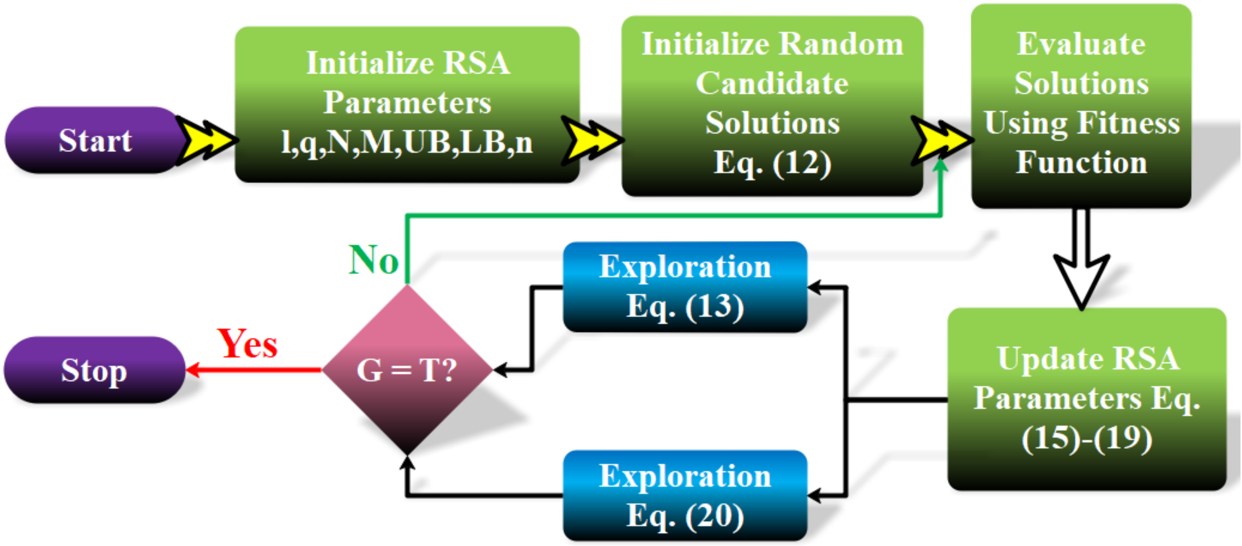

Start
Initialize RSA Parameters l,q,N,M,UB,LB,n
Initialize Random Candidate Solutions Eq. (12)
Evaluate Solutions Using Fitness Function
No
Exploration Eq. (13)
Update RSA Parameters Eq. (15)-(19)
Stop
Yes
G = T?
Exploration Eq. (20)

Fig. 1. Flowchart of RSA.

D. Data Processing

The principal objective of this study is to formulate a robust methodology for the accurate evaluation of students' academic performance, considering various contextual factors that exert influence. To achieve this goal, meticulous preprocessing of the initial dataset is imperative. In this research, a dataset related to education in Portugal was employed, consisting of 33 distinct characteristics [47], [48] [49]. These features were selected to effectively depict the academic performance of a total of 395 students, considering the information and circumstances of each individual throughout the academic period. The initial step involves the conversion of textual data into numerical values, a foundational prerequisite for the execution of machine learning tasks, facilitating effective data analysis and the application of advanced statistical techniques. The dataset encompasses a diverse range of variables with potential impacts on academic outcomes, including sex, school, urban or rural residency (address), age, family size (famsize), guardian, parental cohabitation status (Pstatus), parental education and occupations (Medu, Fedu, Mjob, and Fjob), home-to-school travel time (traveltime), weekly study time (studytime), school choice motivation (reason), current health status, past class failures (failures), weekday (Dalc), and weekend (Walc) alcohol consumption, engagement in extra paid classes, participation in supplementary education (schoolsup), family educational support (famsup), attendance at nursery school, involvement in extracurricular activities, aspirations for higher education, access to the internet, student absences, involvement in romantic relationships, quality of family relationships, free time, and frequency of socializing. To optimize the dataset's suitability, the preprocessing phase incorporated the application of random permutation (randperm) to mitigate biases, along with normalization procedures aimed at standardizing parameter scales. This research aims to predict and categorize students' academic performance, utilizing the G1 and G3 variables, with G3 representing final grades segmented into four distinct levels: Excellent (16–20), Good (14–16), Acceptable (12–14), and Poor (0–12). The methodology seeks to establish a comprehensive framework for comprehending and assessing academic performance within various contextual factors, contributing to improvements in educational practices and policy development. Fig. 2, presented in the article, illustrates a correlation matrix detailing relationships among input and output variables, highlighting the positive influence of parental education, especially maternal education, on academic performance. Additionally, factors such as daily and weekly alcohol consumption, prior academic failures, and student age demonstrate discernible impacts on school grades, underscoring the critical importance of both study time and parental education as pivotal factors contributing to academic success.

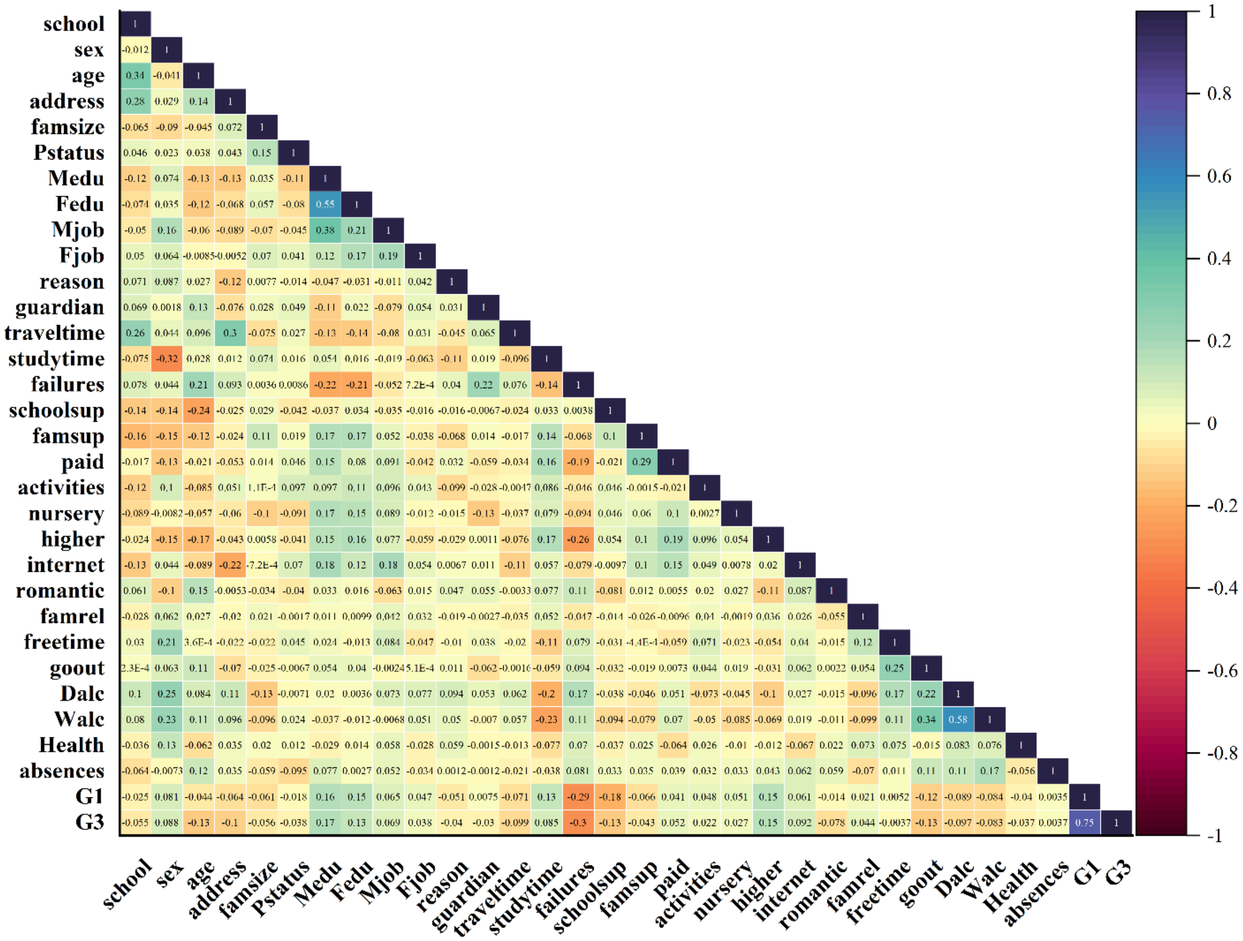


Fig. 2. Correlation matrix for the input and output variables.

III. Results and Discussion

A. Evaluation of Models' Applicability

In the evaluation of classification problems, the metric commonly employed to assess a model's overall performance is Accuracy. This metric relies on four key components: True Positives (TP) for correct positive predictions, True Negatives (TN) denoting accurate negative predictions, False Positives (FP) representing inaccurate positive predictions, and False Negatives (FN) indicating incorrect negative predictions. However, the applicability of Accuracy diminishes in scenarios involving imbalanced data, where it tends to favor the majority class, limiting its interpretability. To overcome this limitation, three additional evaluation metrics, including Recall, F1-Score, Precision, Matthew’s correlation coefficient (MCC), and Area under the curve (AUC), are frequently utilized. These metrics offer a more nuanced understanding of a model's performance, particularly in the presence of imbalanced class distributions. Expressed through mathematical equations, typically numbered from 22 to 26, these metrics collectively contribute to a refined and comprehensive assessment of the effectiveness of a classification model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (22)$$

$$Precision = \frac{TP}{TP+FP} \quad (23)$$

$$Recall = TPR = \frac{TP}{P} = \frac{TP}{TP+FN} \quad (24)$$

$$F1\_score \ = \frac{2\times Recall \times Precision}{Recall+Precision} \quad (25)$$

$$MCC \ = \frac{(TP*TN)-(FP+FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (26)$$

B. Hyperparameters and Convergence Results

In machine learning, hyperparameters, external configurations that encompass elements such as learning rates and regularization strengths, play a pivotal role in shaping a model's behavior. Unlike parameters, hyperparameters are predetermined and are not directly acquired from the data. The optimization of model performance hinges on the essential process of tuning hyperparameters, demanding experimentation, and the application of optimization techniques. Table II meticulously delineates the hyperparameter values associated with ETRS and ETGT models, specifically max_depth, min_samples_split, min_samples_leaf, and max_leaf_nodes. This comprehensive presentation significantly bolsters the transparency and reproducibility of models in machine learning research, offering crucial insights for a more profound comprehension and accurate replication of model configurations.

TABLE II. RESULTS OF HYPERPARAMETERS

Target	Hyperparameter	ETRS	ERGT
G1	max_depth	24	722
	min_samples_split	0.028	0.511
	min_samples_leaf	0.0125	0.092
	max_leaf_nodes	250	10
G3	max_depth	275	975
	min_samples_split	0.001	0.234
	min_samples_leaf	0.0015	0.0631
	max_leaf_nodes	4790	10

This research endeavors to optimize the Extra-Trees Classifier's (ETC) hyperparameters, tailoring its performance to specific datasets and problem domains. The optimization process involves utilizing the Gorilla Troops Optimizer (GTO) and Reptile Search Algorithm (RSA), representing a substantial advancement in enhancing the predictive capabilities of this foundational machine learning algorithm. Evaluating the optimization performance involves assessing how selected algorithms impact the Accuracy of ETC through iterations. Fig. 3 depicts two convergence curves, namely ETRS and ETGT, using a stair form with four steps of 50 iterations each. In G1 prediction, ETRS initiates with lower accuracy, but within the first 90 iterations, it consistently outperforms ETGT. The dynamics reverse in the second stage, and after the 90th iteration, both models perform similarly. Notably, around the 125th iteration, ETRS exhibits a marked increase in Accuracy. Conversely, in G3 estimation, both models start with similar Accuracy values. ETRS outperforms ETGT from 0 to 25 iterations, and then ETGT surpasses ETRS from 25 to approximately 75 iterations. Between 75 and 120 iterations, the performance of both models aligns. After the 125th iteration, ETRS experiences a distinctive surge, ultimately concluding the convergence process with a higher accuracy rate than the ETGT model.

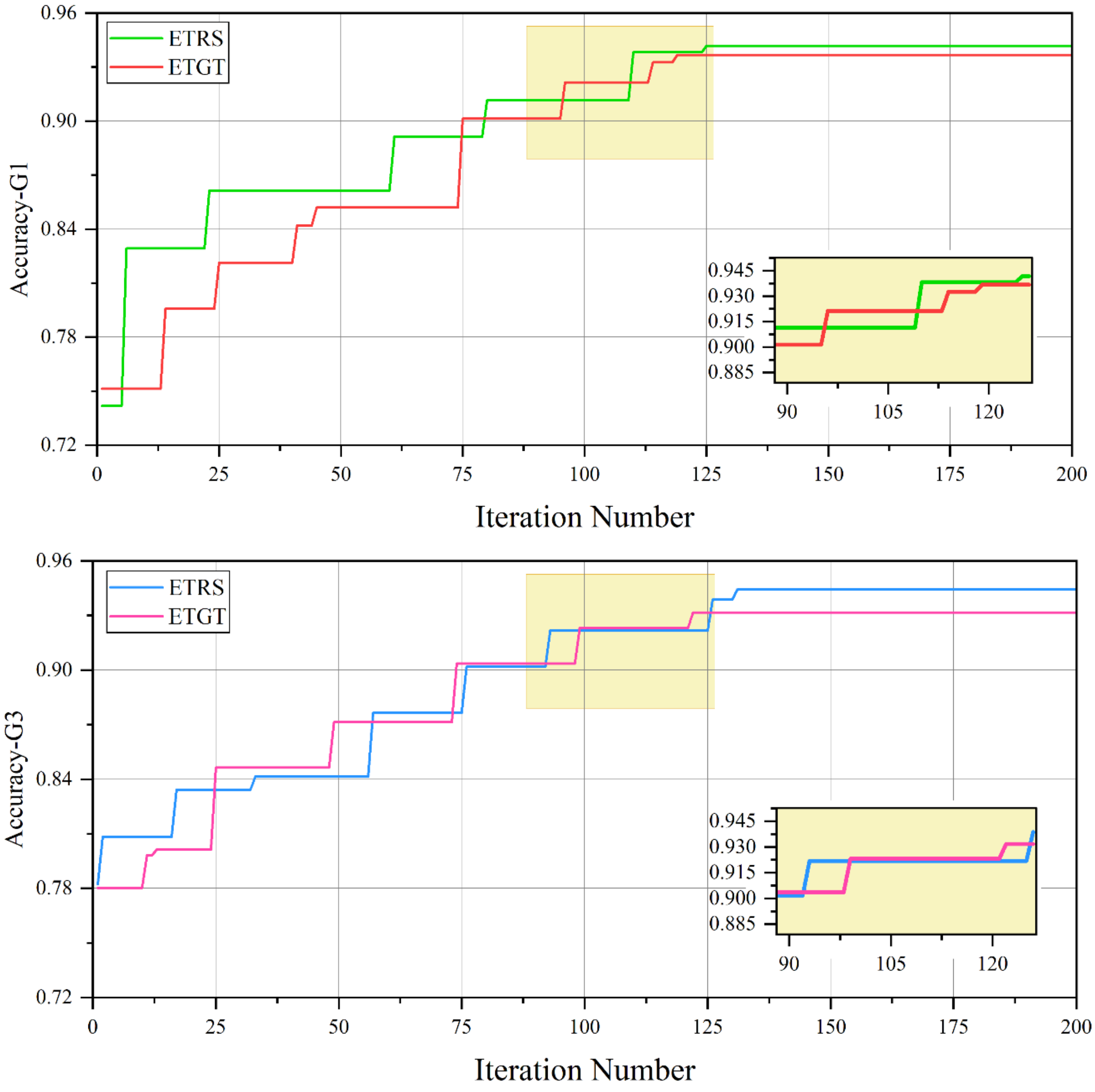


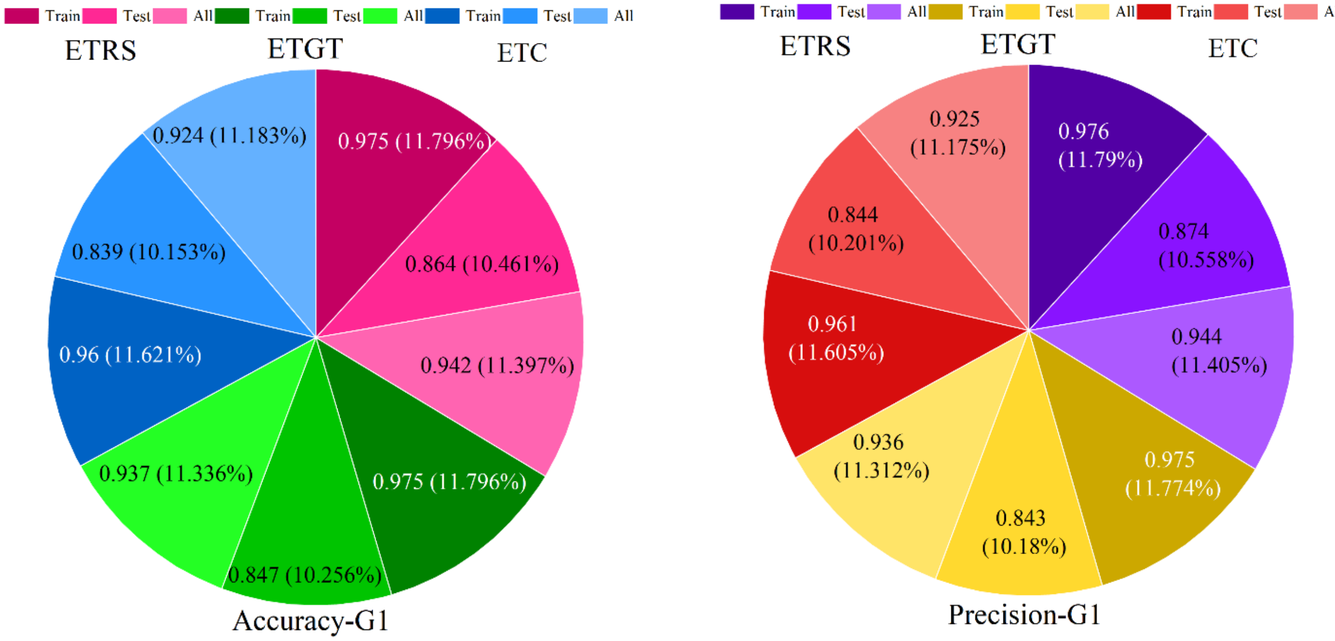
Fig. 3. Convergence curve of models. Prediction and classification results.

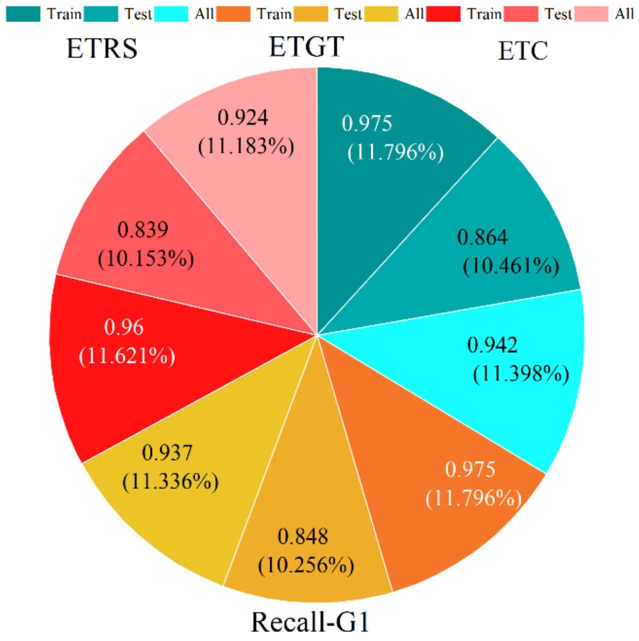
In the pursuit of predicting future academic achievements in mathematics through machine learning algorithms, this investigation integrates a diverse array of student information, with a specific emphasis on their short-term and final grades (G1 and G3). The dataset assumes a pivotal role in the training and evaluation of three models based on Extra-Trees Classifier (ETC), namely ETC, ETRS, and ETGT. Within this section, the study systematically computes performance metrics such as Accuracy, Precision, Recall, F1-score, MCC, and AUC at each prediction stage. This meticulous analysis aims to discern the most effective prediction model, offering valuable insights for enhancing students' academic success. All relevant metric values, encompassing all, train, test, and model, are detailed in Table III and illustrated in Fig. 4.

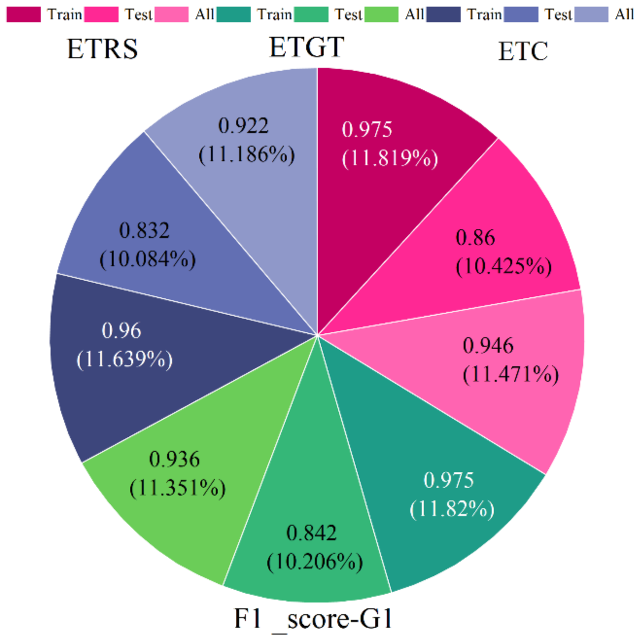
Regarding G1 prediction, ETRS and ETC exhibit the strongest and weakest prediction performance, achieving maximum and minimum Accuracy values of 0.975 and 0.839, respectively. ETRS attains maximum Precision, Recall, F1-score, MCC, and AUC values of 0.976, 0.975, 0.975, 0.957, and 0.931, affirming its high accuracy in positive predictions. The performance of the other hybrid model (ETGT) aligns with ETRS in the training phase Accuracy but experiences a lower value in the testing phase. For G3 prediction, the comparison among the three models reveals ETRS as the strongest predictor with maximum Accuracy, Recall, and F1-score values of 0.953 and 0.921 for MCC. ETGT, with a 0.7% lower Accuracy, secures the second position in the ranking when compared to ETC.

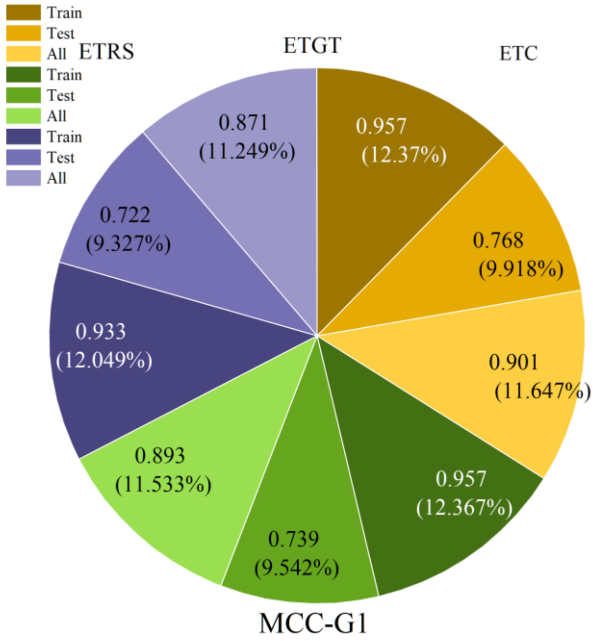
TABLE III. RESULT OF PRESENTED MODELS

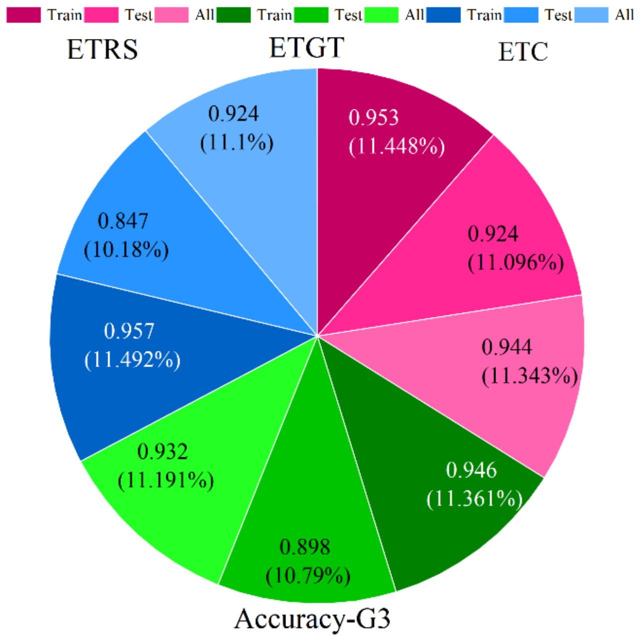
Target	Model	Section	Index values					
			Accuracy	*Precision*	*Recall*	*F1 _Score*	*MCC*	*AUC*
G1	ETC	Train	0.960	0.961	0.960	0.960	0.932	0.913
		Test	0.839	0.844	0.839	0.832	0.722	
		All	0.924	0.925	0.924	0.922	0.871	
	ETRS	Train	0.975	0.976	0.975	0.975	0.957	0.931
		Test	0.864	0.874	0.864	0.860	0.768	
		All	0.942	0.944	0.942	0.946	0.902	
	ETGT	Train	0.975	0.975	0.975	0.975	0.957	0.936
		Test	0.847	0.843	0.848	0.842	0.739	
		All	0.937	0.936	0.937	0.936	0.893	
G3	ETC	Train	0.957	0.957	0.957	0.956	0.926	0.922
		Test	0.847	0.851	0.848	0.844	0.737	
		All	0.924	0.924	0.924	0.923	0.871	
	ETRS	Train	0.953	0.955	0.953	0.953	0.921	0.945
		Test	0.924	0.924	0.924	0.923	0.872	
		All	0.944	0.946	0.944	0.944	0.906	
	ETGT	Train	0.946	0.946	0.946	0.946	0.908	0.932
		Test	0.898	0.900	0.898	0.896	0.827	
		All	0.932	0.933	0.932	0.931	0.884	




Train
Test
All
Train
Test
All
Train
Test
All
ETRS
ETGT
ETC
0.975
(11.796%)
0.864
(10.461%)
0.942
(11.398%)
0.975
(11.796%)
0.848
(10.256%)
0.937
(11.336%)
0.96
(11.621%)
0.839
(10.153%)
0.924
(11.183%)
Recall-G1


Train
Test
All
Train
Test
All
Train
Test
All
ETRS
ETGT
ETC
0.975
(11.819%)
0.86
(10.425%)
0.946
(11.471%)
0.975
(11.82%)
0.842
(10.206%)
0.936
(11.351%)
0.96
(11.639%)
0.832
(10.084%)
0.922
(11.186%)
F1 _score-G1


Train
Test
All
ETRS
Train
Test
All
Train
Test
All
ETGT
ETC
0.957
(12.37%)
0.768
(9.918%)
0.901
(11.647%)
0.957
(12.367%)
0.739
(9.542%)
0.893
(11.533%)
0.933
(12.049%)
0.722
(9.327%)
0.871
(11.249%)
MCC-G1


Train
Test
All
Train
Test
All
Train
Test
All
ETRS
ETGT
ETC
0.953
(11.448%)
0.924
(11.096%)
0.944
(11.343%)
0.946
(11.361%)
0.898
(10.79%)
0.932
(11.191%)
0.957
(11.492%)
0.847
(10.18%)
0.924
(11.1%)
Accuracy-G3

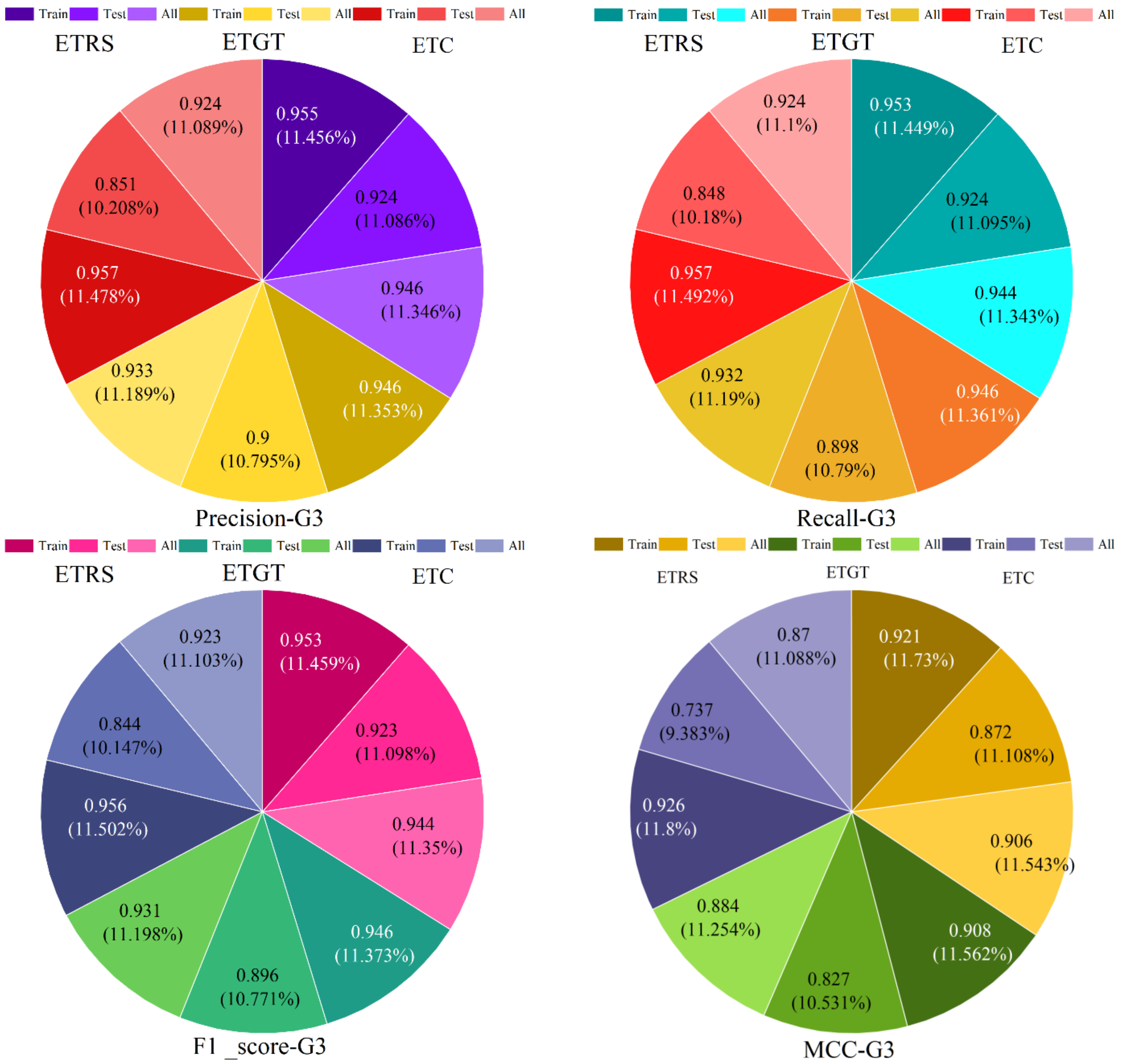


Fig. 4. Pie chart plot for the evaluation of developed models.

Tables IV and V presents the Precision, Recall, F1_score, MCC metrics for students categorized by G1 and G3 grades. These tables offer insights into the model's performance, revealing its accuracy in positive predictions, ability to capture true positives, and overall effectiveness in classifying students based on academic performance levels.

1) G1

a) Excellent: This cohort constitutes around 10% of the dataset, featuring 41 high-achieving students. Despite the ETC and ETRS models exhibiting impeccable Precision (1), the optimized ETGT model shows a slight difference of approximately −5.5%. However, with a Recall value of 0.8293, the ETGT model excels in accurately identifying instances within this top-performing group, surpassing the other models.

b) Good: Among the 54 students in this group, the ETGT model emerged as the superior classifier, achieving Precision, Recall, and F1_score values of 0.9444. Notably, ETRS exhibited the weakest performance based on Precision values, whereas, considering MCC, Recall, and F1-Score, the ETC model demonstrated the least optimal performance levels.

c) Acceptable: The ETRS model showcased superior applicability compared to other models, registering maximum values for all metrics (Precision = 0.984, Recall = 0.912, F1-Score = 0.947, and MCC=0.928). In contrast, the ETGT hybrid model occupied the last position, exhibiting the lowest values across all metrics.

d) Poor: This group pertains to students who have faced academic failure, and the 232 students classified within this category demand heightened institutional focus for improvement. Notably, the performance of all models in classifying this group proves to be optimal, surpassing the other three classes with Precision exceeding 90%. Once again, ETRS stands out as the best model, exhibiting the highest metric values in this context.

TABLE IV. EVALUATION INDEXES OF THE DEVELOPED MODELS' PERFORMANCE IN G1

Model	**Grade**	**Index values**			
		Precision	***Recall***	***F1-score***	***MCC***
ETC	Excellent	1.000	0.805	0.892	0.873
	Good	0.878	0.796	0.835	0.812
	Acceptable	0.922	0.868	0.894	0.892
	Poor	0.924	0.991	0.956	0.887
ETRS	Excellent	1.000	0.781	0.877	0.937
	Good	0.839	0.870	0.855	0.831
	Acceptable	0.984	0.912	0.947	0.928
	Poor	0.947	0.996	0.971	0.872
ETGT	Excellent	0.9444	0.8293	0.8831	0.847
	Good	0.9444	0.9444	0.9444	0.935
	Acceptable	0.8923	0.8529	0.8722	0.906
	Poor	0.9458	0.9784	0.9619	0.873

2) G3

a) Excellent: This subset comprises 40 high-achieving students, representing nearly 10% of the entire dataset under scrutiny. While the Precision values imply that the standalone ETC model showcases flawless predictive capability with a score of 0.971, the optimized models exhibit slightly higher scores (less than 1%). However, a thorough evaluation based on MCC, Recall and F1- score underscores the superiority of the ETRS model, attaining values of 0.883 0.9 and 0.9351.

b) Good: Among this cohort of 60 students, representing 15% of the total 395 studied students, the ETGT model showcased superior performance, particularly evident in Precision values. Furthermore, a comprehensive evaluation considering MCC, Recall and F1-Score affirmed the model's excellence, boasting MCC, Recall and F1-Score values of 0.9, 0.8667 and 0.9123, respectively.

c) Acceptable: Upon scrutinizing the outcomes, it is apparent that the Reptile Search Algorithm (RSA) outperformed the Gorilla Troops Optimizer (GTO) in optimizing the Extra-Trees Classifier (ETC) for G3 classification. The RSA demonstrated higher success, yielding a Recall of 0.9516 and an F1-score of 0.908.

d) Poor: In the classification of students within the Poor category, the ETRS model demonstrated superior performance among the three models. It achieved maximum values across all metrics, notably excelling in the Recall evaluator with a value of 0.9828.

TABLE V. EVALUATION INDEXES OF THE DEVELOPED MODELS' PERFORMANCE IN G3

Model	**Grade**	**Index values**			
		Precision	***Recall***	***F1-score***	***MCC***
ETC	Excellent	0.971	0.825	0.892	0.856
	Good	0.895	0.850	0.872	0.850
	Acceptable	0.885	0.871	0.878	0.885
	Poor	0.934	0.974	0.954	0.884
ETRS	Excellent	0.973	0.9	0.9351	0.883
	Good	0.9245	0.8167	0.8673	0.847
	Acceptable	0.8551	0.9516	0.908	0.942
	Poor	0.9703	0.9828	0.9765	0.929
ETGT	Excellent	0.9722	0.875	0.9211	0.855
	Good	0.963	0.8667	0.9123	0.900
	Acceptable	0.8852	0.871	0.878	0.880
	Poor	0.9303	0.9742	0.9518	0.914

C. Discussion

1) G1: In Fig. 5, the visual representation illustrates the distribution of students across categories, enabling a comprehensive comparison between measured data and the outcomes of classification effectiveness. Specifically focusing on forecasting student performance in G1 scores, individual graphs for each category (Poor, Acceptable, Good, and Excellent) are presented. It is noteworthy that, as per the studied dataset, the total number of students amounts to 395. The subsequent sections meticulously evaluate the models based on recorded figures, revealing 232 individuals in the Poor category, 68 in the Acceptable category, 54 in the Good category, and 41 in the Excellent category. The ETRS model emerges as the most effective classifier for the Poor and Acceptable categories, showcasing precise predictions. However, in the Good and Excellent groups, notable differences are observed between the two hybrid models, with ETRS displaying weaker performance in classifying datasets for these higher-performing groups.

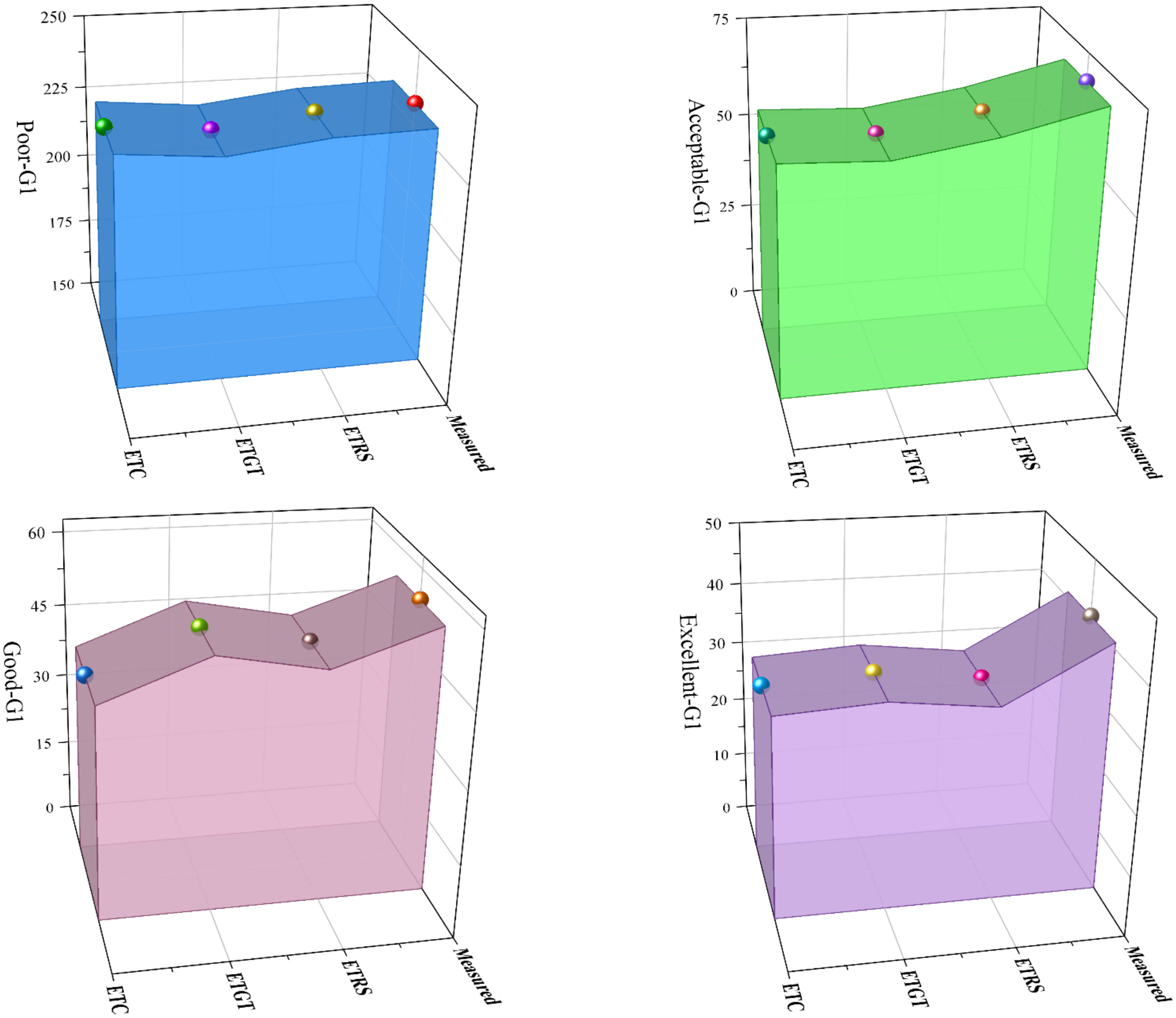
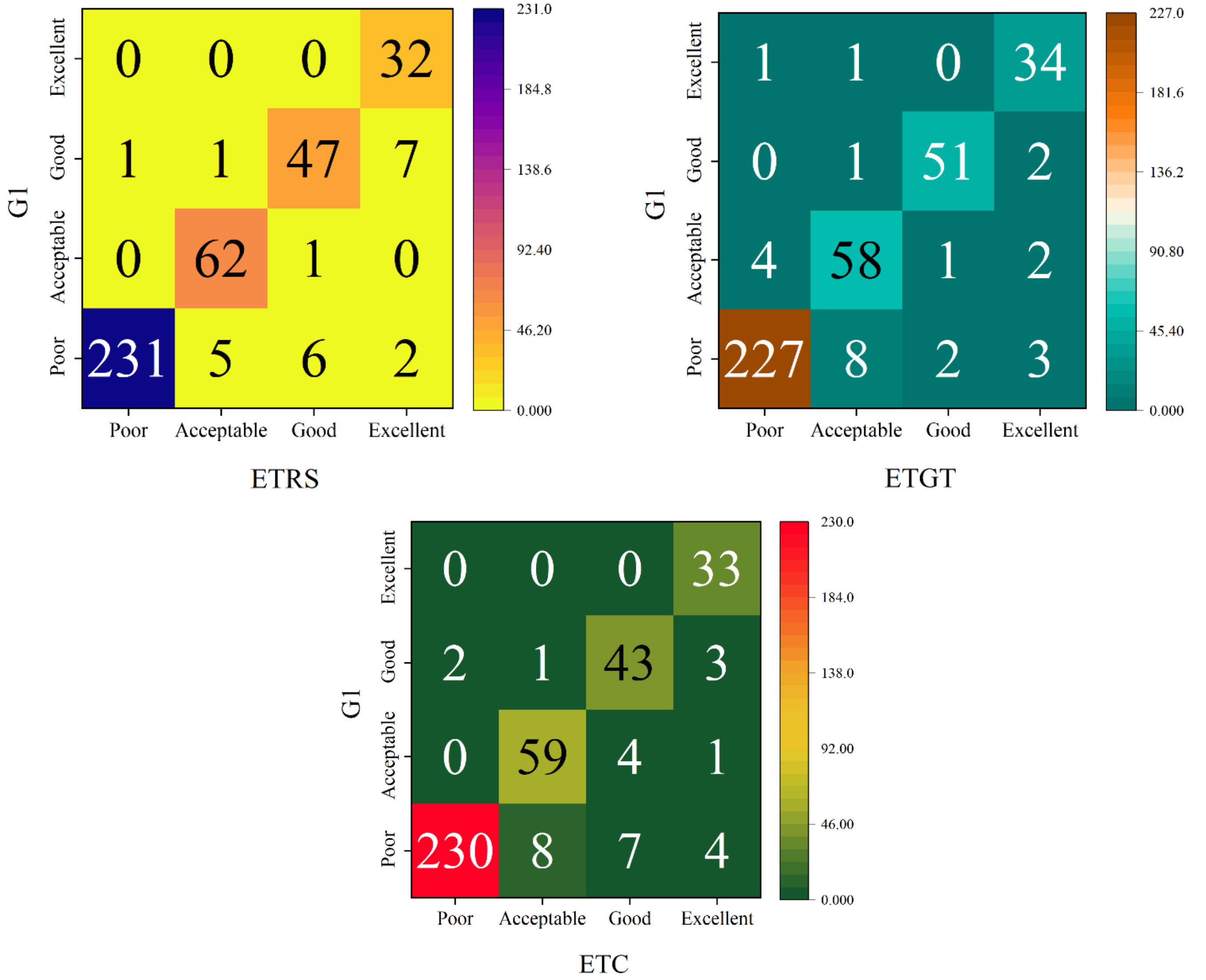


Fig. 5. 3D wall plot for the developed models' accuracy for G1.

Fig. 6 presents a confusion matrix, offering insights into the accurate categorization of students and instances of misclassifications. Within the ETRS model, 372 students were accurately classified across grades, including 32 in Excellent, 47 in Good, 62 in Acceptable, and 231 in Poor, with 23 misclassifications. In contrast, the ETGT model had 25 misclassifications, while the straightforward ETC model accurately classified 365 students and misclassified 30 students.

2) G3: According to Fig. 7, the recorded student figures for the Poor, Acceptable, Good, and Excellent categories were 233, 62, 60, and 40, respectively. Interestingly, the standalone ETC model demonstrated superior performance in the Poor and Good categories compared to the two hybrid models. Subsequently, the ETRS model emerged as the more effective classifier, excelling in the categorization of students into Excellent and Acceptable groups.



ETRS

G1	Poor	Acceptable	Good	Excellent
Excellent	0	0	0	32
Good	1	1	47	7
Acceptable	0	62	1	0
Poor	231	5	6	2

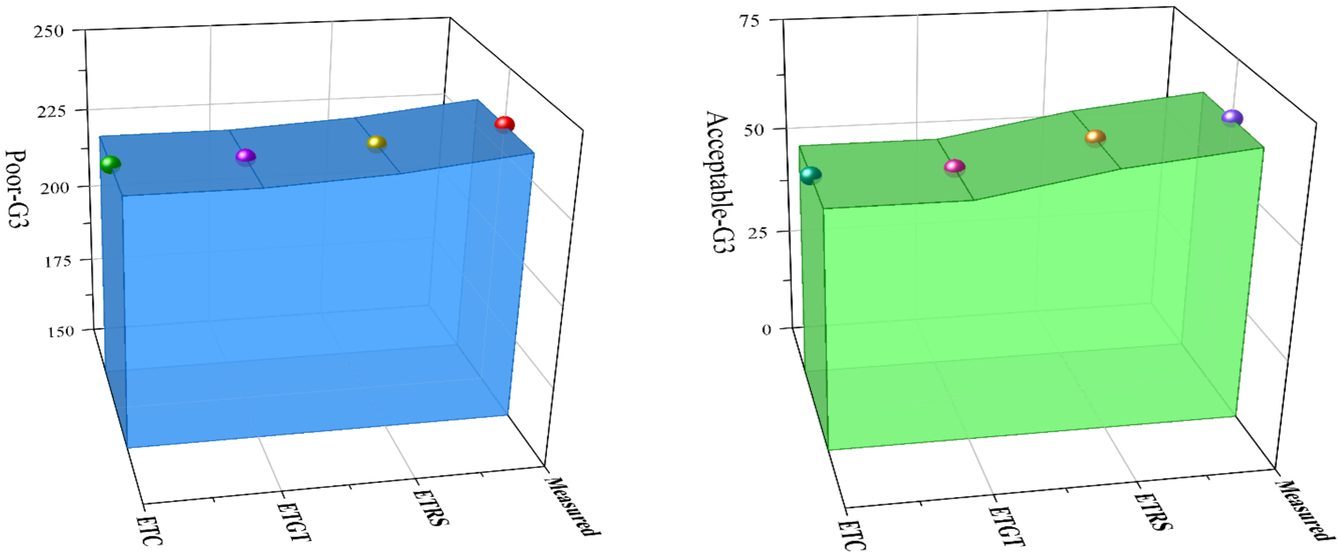
ETGT

G1	Poor	Acceptable	Good	Excellent
Excellent	1	1	0	34
Good	0	1	51	2
Acceptable	4	58	1	2
Poor	227	8	2	3

ETC

G1	Poor	Acceptable	Good	Excellent
Excellent	0	0	0	33
Good	2	1	43	3
Acceptable	0	59	4	1
Poor	230	8	7	4

Fig. 6. Confusion matrix for each model’s accuracy for G1.



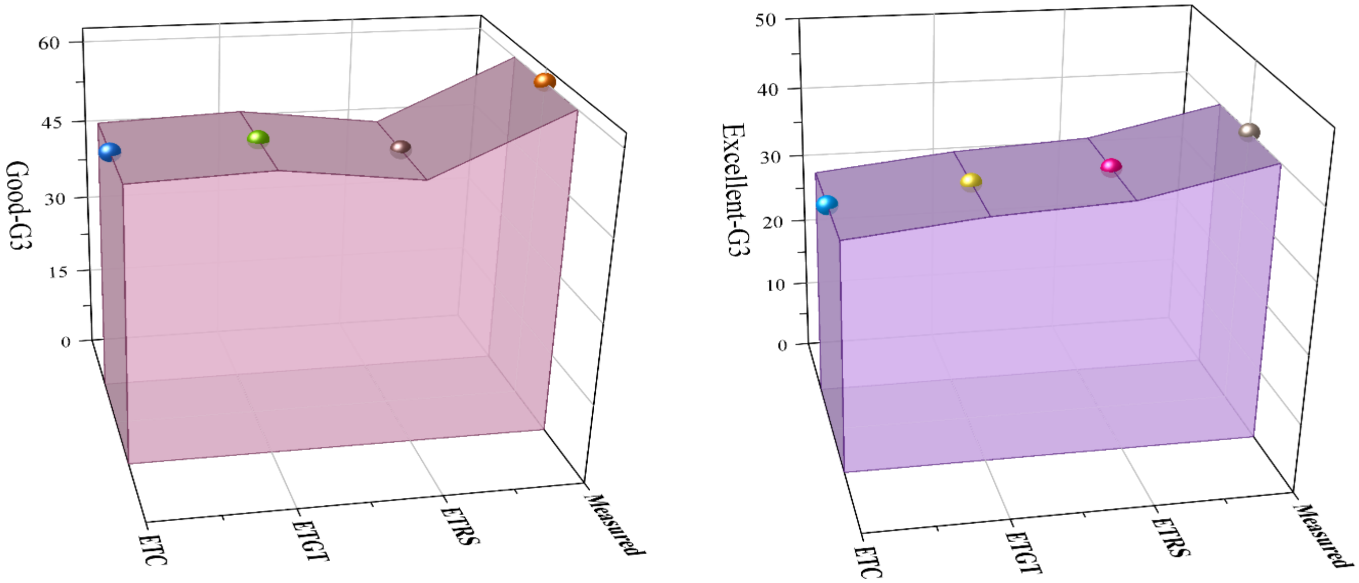


Fig. 7. 3D wall plot for the developed models' accuracy for G3.

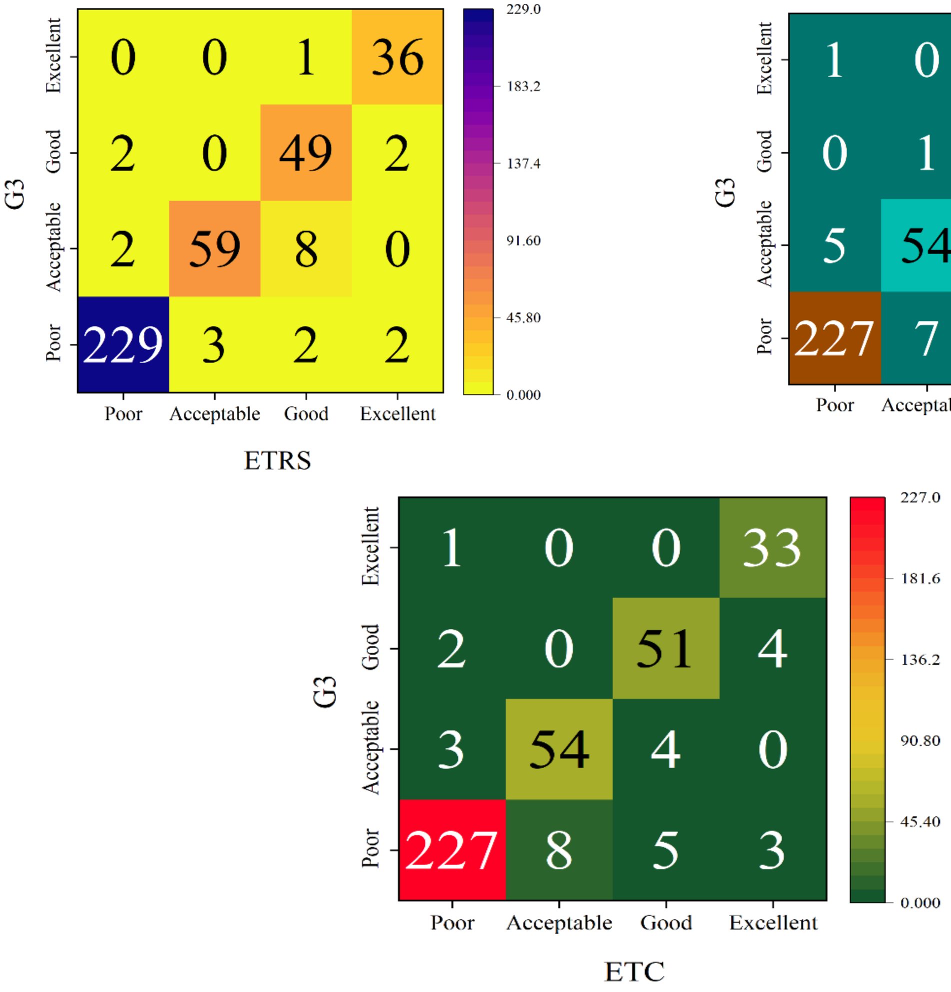


Fig. 8. Confusion matrix for each model's accuracy for G3.

Examining Fig. 8, the ETRS model accurately categorized 373 students into their respective grades, with only 22 misclassifications. In contrast, the ETGT model achieved 368 correct predictions but experienced 27 misclassifications. A thorough comparison reveals that the ETRS model outperformed both the ETGT and ETC models in terms of overall performance.

D. *Comparing Previous Studies vs. Present Research Study*

Table VI summarizes the results of four existing studies in the field of student performance. According to these works, the highest accuracy was related to the employment of the DTC model in the Nguyan and Peter's study [33] with 82%, while in the present study, the combination of ETC model and RSA algorithm, achieved high value of 0.975 for G1 and 0.953 for G3. As can be seen, this work reached the highest accuracy among others.

TABLE VI. COMPARING RESULTS OF EXISTING STUDIES AND PRESENT WORK

Author (s)	**Models**	**Accuracy**
Kabakchieva [39]	DTC	72.74%
Bichkar and R. R. Kabra [35]	DTC	69.94%
Nguyen and Peter [33]	DTC	82%
Edin Osmanbegovic et al. [37]	NBC	76.65%
Present study for G1	ETRS	0.975
Present study for G3	ETRS	0.953

E. *Generelizability and Limitation of Proposed Model*

It is acknowledged that our study was conducted on a specific dataset and that the results may not be directly applicable to other educational contexts. However, it is believed that the potential to be generalized to other settings is possessed by the proposed approach of combining the ETC model with optimization algorithms, as long as the following conditions are met: The data is sufficiently large and representative of the target population The data contains relevant features that can capture the factors influencing students' academic performance The data is preprocessed and cleaned to ensure its quality and validity The optimization algorithms are tuned and adapted to the characteristics of the data.

The optimization algorithms are powerful tools that can improve the performance of predictive models, but they also have some limitations that need to be taken into account. Some of the common limitations and potential drawbacks of optimization algorithms are then discussed, such as:

- The dependence on the quality and quantity of the data. The data is relied on by optimization algorithms to learn and optimize the objective function, but the data may not be sufficient, representative, or accurate enough to capture the true complexity and variability of the problem domain. This may lead to overfitting, underfitting, or bias in the optimization results. Iterative processes are often involved by optimization algorithms that require a large amount of computation and memory resources, especially for high-dimensional and nonlinear problems.
- This may limit the applicability and efficiency of the optimization algorithms in real-world scenarios, where time and space constraints are important factors.
- The sensitivity to the choice of parameters and initial conditions.
- Optimization algorithms often have several parameters and initial conditions that need to be specified by the user or tuned by some methods.
- The convergence, stability, and quality of the optimization results may have a significant impact on these parameters and initial conditions, but they may not be easy to determine or adapt to different problems or datasets.
- The lack of guarantees and robustness.

IV. CONCLUSION

In the context of education, the deployment of data-driven predictive models takes center stage in this investigation. It accentuates the critical need to integrate both qualitative and quantitative factors for the prediction and evaluation of students' academic performance. Illustrating the effectiveness of data mining methodologies like clustering, classification, and regression, the study addresses the multifaceted challenges proactively encountered by undergraduate students. The insights gleaned offer valuable guidance for policymakers, educational institutions, and students alike, with the shared objective of enhancing future academic outcomes. Moreover, the study introduces a cutting-edge strategy by merging the Extra-Trees Classifier (ETC) model with optimization algorithms, namely Gorilla Troops Optimizer (GTO) and Reptile Search Algorithm (RSA). This innovative approach demonstrates the potential of combining machine learning techniques and optimization algorithms to enhance the precision and effectiveness of predictive models. The outcome is a resilient toolkit designed to tackle the dynamic challenges inherent in students' academic journeys. The comprehensive evaluation undertaken in the study, involving the division of models into training and testing sets, unveils the considerable potential of these hybrid models to augment the classification capabilities of the ETC model. This improvement manifests in noteworthy enhancements in Accuracy and Precision. Upon scrutinizing the results, it becomes apparent that the recognition of the potential to significantly enhance the classification capabilities of the ETC model by these hybrid models is growing. In the context of G1 values, the enhancement of Accuracy, Recall, and F1-Score, achieved through the implementation of RSA and GTO optimization algorithms on the ETC model, was notable. The utilization of RSA and GTO resulted in a 1.56% improvement. The ETRS model, showcasing a remarkable Accuracy rate of 0.975, effectively and precisely classified the majority of students.

On the other hand, the ETGT and ETC models experienced misclassification rates of 6.33% and 7.6%, respectively. Turning attention to G3 values, the application of RSA and GTO optimization algorithms to the ETC model yielded significant improvements in all metrics' values in the testing phase. Nonetheless, this application led to a small reduction in the results of the training phase. The rate of Accuracy values' enhancement for RSA was 9.09%, and for GTO was 6.02% in the testing phase. When the 395 students were categorized based on their final grades, the prowess of the RSA algorithm in enhancing classification Accuracy became evident. The ETRS model demonstrated an impressive Accuracy rate of 0.953, adeptly classifying the majority of students. These findings underscore the efficacy of both RSA and GTO optimization algorithms in refining the predictive capabilities of the ETC model. Notably, the RSA algorithm exhibited a particularly commendable performance, showcasing its exceptional ability to enhance Accuracy, especially in the classification of students based on final grades (G3). The results suggest that the integration of these optimization algorithms holds promise for refining and optimizing the performance of models in educational contexts, contributing to more accurate and reliable student classifications.

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Real-Time Airborne Target Tracking using DeepSort Algorithm and Yolov7 Model

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Abstract—**In light of the explosive growth of drones, it is more critical than ever to strengthen and secure aerial security and privacy. Drones are used maliciously by exploiting some gaps in artificial intelligence and cybersecurity. Airborne target detection and tracking tasks have gained paramount importance in various domains, encompassing surveillance, security, and traffic management. As airspace security systems aiming to regulate drone activities, anti-drones leverage mostly artificial intelligence and computer vision advances in the used detection and tracking models to perform effectively and accurately airborne target detection, identification, and tracking. The reliability of the anti-drone systems relies mostly on the ability of the incorporated models to satisfy an optimal compromise between speed and performance in terms of inference speed and used detection evaluation metrics since the system should recognize the targets effectively and rapidly to take appropriate actions regarding the target. This research article explores the efficacy of DeepSort algorithm coupled with YOLOv7 model in detecting and tracking five distinct airborne targets namely, drones, birds, airplanes, daytime frames, and buildings across diverse contexts. The used DeepSort and Yolov7 models aim to be used in anti-drone systems to detect and track the most encountered airborne targets to reinforce airspace safety and security. The study conducts a comparative analysis of tracking performance under different scenarios to evaluate the algorithm's versatility, robustness, and accuracy. The experimental results show the effectiveness of the proposed approach.**

Keywords—Real-time detection; target tracking; anti-drone; Artificial Intelligence; Computer Vision

I. Introduction

The importance of addressing aerial privacy and security issues associated with drones is growing steadily, emphasizing the critical importance and need for reliable target detection and tracking models for effective airspace security systems, such as anti-drone systems.

The deployment of an anti-drone system, which is known also as a counter-drone system depends mostly on the performance of the detection and tracking modules to detect and identify the most encountered airborne targets to avoid triggering false alarms [1], [2]. It is important to note that the detection and identification tasks are very crucial for the success of the anti-drone process and mainly to avoid neutralizing friendly airborne targets such as birds. Thus, the anti-drone system should recognize the target properly without confusion that could cause weighty damage during the interception phase [3]. Airborne target detection and tracking is crucial in numerous applications, including defense, civilian security, and urban planning. An anti-drone system's effectiveness depends significantly on the detection of the encountered airborne targets [3], [4], [5]. It is important that an anti-drone recognizes and distinguishes between the main types of airborne targets. They share the same airspace and altitudes; mostly the low altitude airspace up to 32 000ft as an upper limit. Due to their similarity, recognizing flying targets at this altitude becomes a real challenge, which increases the probability of false detection. To reinforce and improve the anti-drone process, there is a need to develop suitable detection and tracking models able to meet the requirements and the existing needs. There are several challenges related mainly to the complexity of recognizing effectively and rapidly drones and other airborne targets present in the sky sharing many characteristics with drones that mislead the system. Further, the research tasks related to tracking multiple airborne targets have not been thoroughly studied in the existing literature.

In this study, we aim to develop an advanced detection and tracking model that can identify and track the most common targets in the sky. Computational experiments are conducted through the training, validation, and testing of a model on real-world data. This model is practical based on computational results. Therefore, integrating DeepSort with YOLOv7 is promising due to its real-time object detection capabilities and tracking precision. In addition, using DeepSort for tracking coupled with YOLOv7 for detection offers a significant approach compared to individual applications of these models. This research article aims to contribute to advancing airborne target tracking technology, evaluating the DeepSort with YOLOv7 algorithm's effectiveness in tracking diverse targets under varying scenarios. In the following, Section II provides a summary of the research studies on airborne target detection and tracking, whereas the solving methodology and experimental setup are presented in Section III. The experimental details and results are highlighted in Section IV. We conclude by discussing the advantages and limitations of the proposed model in Section V.

II. Literature Review

This section delineates existing methods for airborne target tracking, emphasizing the advancements and limitations. It covers various algorithms and their applications in tracking airborne targets.

The rise of Artificial Intelligence (AI) has improved many conventional applications, systems and tasks in several domains such as, autonomous cars, smart cities, smartphones, smart truck distribution [6] and pandemic detection [7].

Recently, the field of airborne targets detection and tracking has witnessed significant advancements, driven by the outstanding rise of drones across various sectors. Several research studies have addressed the challenges and risks posed by the proliferation of drones, necessitating the development of robust anti-drone systems capable of accurate detection and tracking.

In study [8], the authors present the small drone tracking results using the radar-based range estimation, as well as the receding horizon tracking model of unauthorized drones through the use of the receding horizon maximization technique and the fisher information matrix predictive model. Combining these two approaches yields the best localization results. The tracking approach proposed in study [9] uses a time difference of arrival estimation algorithm based on Gauss priori probability density functions with Kalman filters. The combination of these models achieved good results for drone tracking. Also, the paper in [10] has proposed a tracking model which analyses the generated acoustic signatures of the drones using beamforming algorithm. The conducted experiments show that depending on the type of the drones, they can be tracked up to 250 meters. Further, a radar tracking and detection method based on phase-interferometry and joint range-Doppler-azimuth processing is presented in study [11]. All of the extracted features from the developed model are used to classify drones. Another drone position tracking proposed in study [12] uses the received signal strength indication (RSSI) signals to estimate the distance and angle of the target to track the aerial target. It uses the estimated distance and angle to gradually track the target through the incorporation of CDQA and ADCA algorithms. The implementation of the proposed approach is not implemented on real environment.

The combination of DeepSort and Yolo has been used in different detection and tracking applications. The authors in study [13] have used a combination of YOLOv3 and RetinaNet for generating detections in each frame along with DeepSort algorithm to track multiple objects from a drone-mounted camera. Comparing the results of the experiment with the existing state-of-the-art models, the detection and tracking combination shows competitive performances on VisDrone 2018 dataset. Similarly, the paper [14] has proposed to use Yolov4 to detect and localize vehicles within the restricted zone along with DeepSort to track them to reinforce aerial surveillance.

To the best of our knowledge, there has been no study that has utilized DeepSort in conjunction with YOLOv7 to detect and track multiple airborne targets specifically for deployments in anti-drone systems.

However, the existing studies on airborne tracking have shown a limited exploration of the specific research aspect addressed in this study, specially tracking the most common airborne targets. The majority of existing research in this domain has predominantly concentrated on drone detection only, with comparatively less emphasis on the comprehensive investigation of the aspect central to our research. Motivated by these limitations and the need for a comprehensive tracking approach, this paper proposes a novel DeepSort algorithm integrated with the YOLOv7 detection model. By combining the real-time detection capabilities of YOLOv7 with the robust object association and tracking features of DeepSort, our proposed methodology aims to address the existing gaps and improve the state-of-the-art in airborne targets detection and tracking.

III. Solving Methodology

In this study, we propose the use of DeepSort algorithm with the YOLOv7 model for detecting and tracking the most encountered airborne targets. This methodology section outlines the dataset used, model training process, hyperparameters, and evaluation metrics.

A. Data Collection

Our developed detection and tracking models are trained on the most encountered airborne targets in the sky which anti-drone systems should recognize rapidly and effectively without causing false alarms. We have gathered a diverse dataset containing video and images with labeled bounding boxes around the targets of interest. The airborne targets in the dataset comprise drones, birds, airplanes, daytime frames, and buildings, which reflects the complexity of real-world detection and tracking scenarios. Indeed, we have trained our detection on five airborne target classes, namely drones, birds, airplanes, dayframes, and buildings. The images are collected mainly from [15], [16], [17] and annotated according to the Yolo format: object class, x, y, width, and height in the corresponding annotation text files. Following, we have used videos from [18] to perform the tracking process. The provided videos highlight mostly drones in different contexts and under different conditions Furthermore, the used dataset ensures variability in lighting conditions, backgrounds, sizes, orientations, and occlusions to improve the used algorithm's performance and robustness.

B. DeepSort Model

Deep Simple Online and Real-time Tracking (DeepSort) is primarily a tracking model that works in conjunction with single-shot and two-shot object detection models, such as You Only Look Once (YOLO) to track targets and objects in real-time across frames in a video sequence [19]. The DeepSort is used for multiple target tracking in videos. It combines two main components: a detection model (like YOLO, SSD, or Faster R-CNN) that identifies the targets in each frame from the video, and a tracking algorithm that maintains the identity of these objects across frames and follows closely the motion of the targets. Initially, the detection model identifies the class of the target and generates bounding boxes around these targets, providing also their corresponding positions and labels. Following, DeepSort extracts relevant features from the detected bounding boxes, which represent the visual characteristics and appearance of the targets. The numerical representation of these features is typically created by a neural network that performs the detection and tracking. Furthermore, using these extracted features, DeepSort associates objects detected in different frames. The DeepSort algorithm associates detections across frames. Matching detections and maintaining consistent identities through the consecutive frames is achieved by minimizing costs, such as the Hungarian algorithm. Also, DeepSort uses a prediction mechanism to maintain track of occluded or temporarily undetected objects until they reappear. As a result, temporary occlusions are less likely to occur. For each target identified in the video, DeepSort produces a continuous set of tracks related to their motion. In addition, the generated tracks contain the unique identity of targets across frames, allowing comprehensive analysis of object movement. In this research study, using Yolov7 as input, The DeepSORT algorithm perform tracking of different airborne targets. In situations with dynamic aerial movement and occlusions, DeepSort's capacity to associate and track objects across frames by utilizing appearance features and motion information is essential for preserving identities.

Therefore, in an anti-drone system, YOLOv7 operates as the initial detection module, processing input data to identify potential airborne targets. Detected objects, along with their bounding box coordinates and confidence scores, are then passed to DeepSort for tracking. DeepSort associates detections across frames, maintaining tracks for each identified target. The integrated system continuously analyzes the behavior of airborne targets, enabling real-time monitoring and threat assessment.

C. Experimental Setup

The experiments are conducted on a local machine using a NVIDIA Quadro P4000, an Intel(R) Xeon(R) W-2155@ 3.30GHz with 32GB of main memory, and Windows® as the operating system. As well as that, we have used Pytorch version 1.13.1 along with Cuda 11.6 and Cudnn v8.8 for running the Yolo model. Furthermore, selecting appropriate hyperparameters is crucial for the training and tuning of the developed model. Our process of tuning hyperparameters entails carefully adjusting their corresponding values to find optimal rates. Table I shows the hyperparameters used during training.

TABLE I. THE HYPERPARAMETERS USED

Hyperparameter	Value	Hyperparameter	Value
Epochs	150	Learning rate (lr)	0.01
Batch size	16	Weight decay	0.005
Image size	640×640	Momentum	0.937
Warmup epochs	3	Scale	0.5
Left and right flip	0.5	Translate	0.1

D. Evaluation Metrics

Evaluation metrics for our detection models include the following assessment metrics: Recall (R), Precision (P), Mean Average Precision (mAP), F1 score, and Frames Per Second (FPS). This allows a better evaluation of the developed models for multi-class detection since it utilizes verified and missed detection samples associated with the detection of each class target, such as False Positives (FP), False Negatives (FN), True Positives (TP) and True Negatives (TN). When it comes to P, the relevant detection results are considered, while recall is the total number of correct detections. Equations for determining these evaluation metrics are shown below:

$$R = \frac{\sum TP}{\sum TP + FN} \qquad (1)$$

$$P = \frac{\sum TP}{\sum TP + FP} \qquad (2)$$

For each category, the mean Average Precision represents the overall area under the precision-recall curve.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_n \qquad (3)$$

where, N is the number of target classes and AP_n is the mean mean average precision for each class.

$$FPS = \frac{\sum_{i=1}^{k} I}{Inferencetime} \qquad (4)$$

where, I is the total number of images used in the inference phase.

IV. RESULTS AND DISCUSSION

Using the tracking algorithm DeepSort and our detection model Yolov7, we present the results of the experiments conducted in this section. A detailed analysis of the quantitative metrics follows, providing insights into the strengths of the proposed approach.

A. Detection Performance

As first step, the detection model is run to recognize and identify the airborne targets efficiently and accurately. We have compared several single-shot object detector algorithms [20] to select the suitable model that satisfies the speed performance compromise required for anti-drone deployment. The efficacy of our developed model has been demonstrated in Table II, which details a selection of the experimental results of the most used models, based on detection performance confidence scores and inference speed. Therefore, it is shown that Yolov7 model surpasses the other models based on the provided results of detection metrics and inference speed. Also, the Yolov7 model reaches high accuracy and fast speed, comprises between speed performances. In addition, we have completed the model analysis by comparing the detection performance with respect to the precision and recall of each class in Table III. Indeed, it is shown that the model effectively detects the targets reaching high rates of the used evaluation metrics.

Fig. 1 shows the detection performance of the selected Yolov7 model as well as the generated loss and the behavior at each epoch during the training. The training and validation behaviors of the model are described in detail with respect to the aforementioned metrics; recall, precision, mAP@0.5 and mAP@0.5–0.95, as well as objects, classes and boxes losses. The curves converge to a fixed threshold after training for 150 epochs. Additionally, the model has demonstrated both optimal performance and high generalization ability without bias, variance, or overfitting or underfitting. Training and validation curves have similar behaviors with no gaps between them, and they converge at the same time (≈ 75 epochs). This model proves its effectiveness by continuously recording loss, precision, recall, and mAP metrics during training and validation processes.

As shown in Fig. 2 to Fig. 5, we have generated the evolution of the R, P and F1 curves with respect to the confidence score to provide deeper insight into the model. As can be seen from the curves, birds, drones, and airplane targets have similar and close detection behaviors, except for the building and dayframe classes. The precision, recall, and F1 curves show that the detection performances of all categories are above 90%. The precision-recall curve (see Fig. 3) shows that the model has a 96.8% mAP (area under the curve), which corresponds to a 96.8% precision-recall rate. Also, the precision-recall curve shows that the threshold performance metrics for bird is 0.997, drone 0.973, dayframe is 0.994, airplane 0.959 and building is 0.989. This percentage value also indicates whether the model is able to detect targets while guaranteeing a satisfactory recall and precision rate. As shown in F1-confidence curve (see Fig. 5), the confidence score is set at 0.467, which is important since starting from this point, the metrics are optimized and the performance balance is achieved. Additionally, the F1 curve shows the weighted harmonic of precision and recall, as well as the optimized confidence threshold of 0.467, which is highly required to perform an accurate, real-time detection. Other evaluation criteria such as confusion matrices, inference times, and real-time detection images have emphasized the model's performance. The confusion matrix of our model is shown in Fig. 6. There are five target classes with true positives located along the diagonal in dark blue. According to the true positive values, the proposed model is very effective and efficient at detecting and identifying the types of drones. To make the results more intuitive, we have integrated visualization about the detection performance of the model. Fig. 7 shows the detection of the airborne targets using unseen random images that confirm the model's ability to detect the aforementioned target classes.

TABLE II. EXPERIMENTAL RESULTS OF DETECTION MODELS

Model	Precision	Recall	mAP@0.5	mAP@0.5-0.95	Inference time (ms)
Yolov5	0.916	0.902	0.923	0.701	65.3
Yolov6	0.834	0.87	0.891	0.64	74
Yolov8	0.897	0.868	0.921	0.709	46
Yolov7-d6	0.957	0.928	0.966	0.712	38.5
Yolov7-w6	0.957	0.942	0.968	0.711	29.5
Yolov7	**0.973**	**0.957**	**0.982**	**0.753**	**27.5**

TABLE III. PERFORMANCE OF THE MODEL WITH RESPECT TO EACH TARGET CLASS

Target	Precision	Recall	mAP@0.5	mAP@0.5-0.95
all	0.973	0.957	0.982	0.753
Bird	0.997	0.997	0.997	0.85
Drone	0.956	0.958	0.973	0.549
Dayframe	0.995	0.966	0.994	0.79
Airplane	0.931	0.959	0.959	0.776
Building	0.989	0.912	0.989	0.798

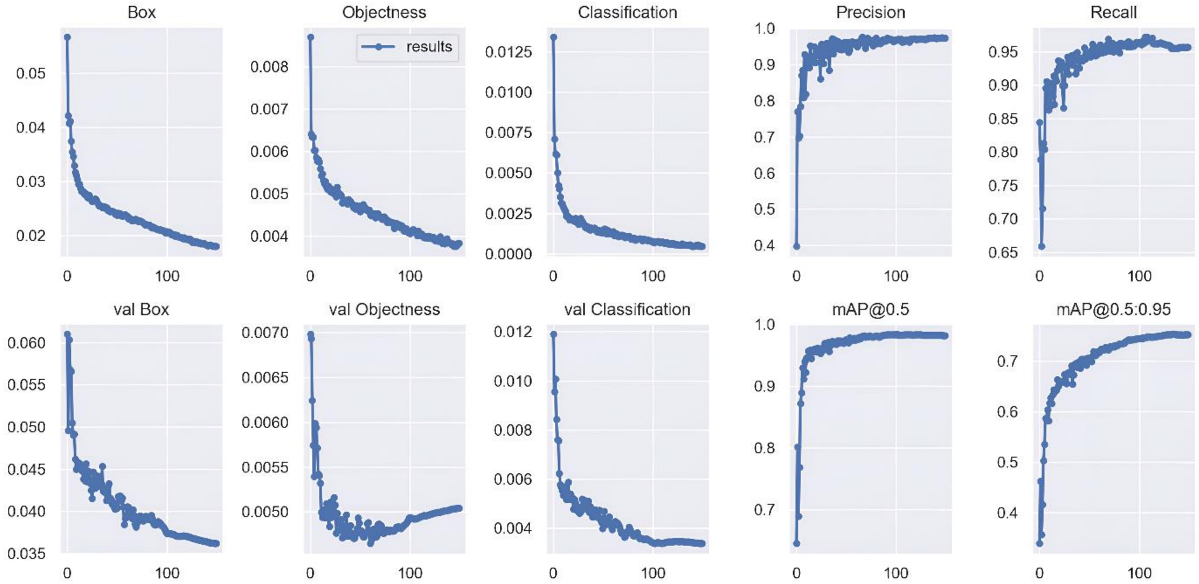


Fig. 1. Performance behavior of the improved model.

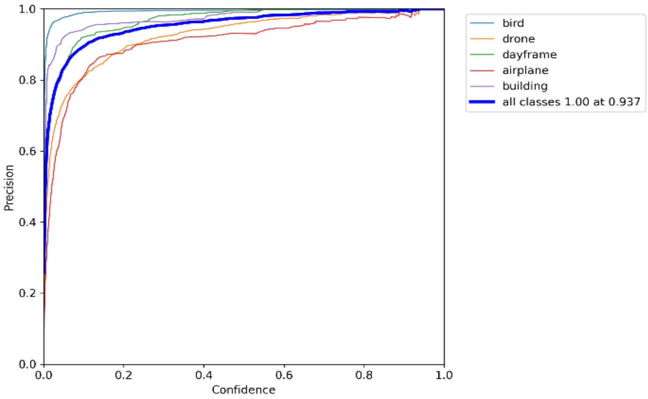


Fig. 2. Evolution of the performance of Yolov7 model with respect to Precision evolution curve over the target classes.

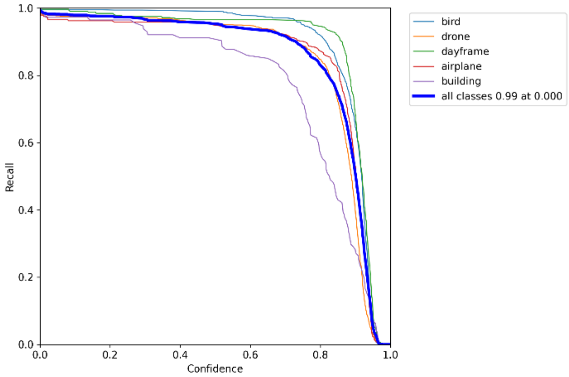


Fig. 3. Evolution of the performance of the Yolov7 model with respect to Precision- Recall evolution curve over the target classes.

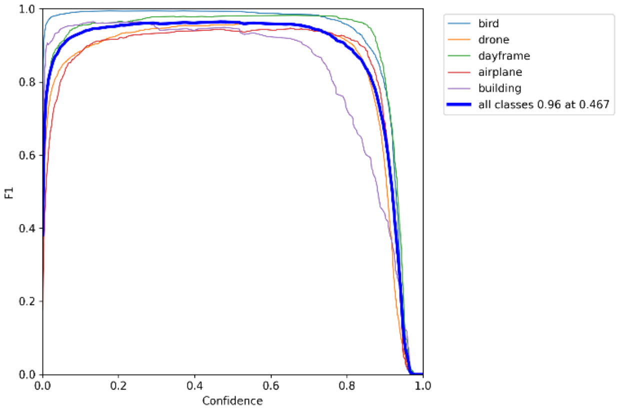


Fig. 4. Evolution of the performance of Yolov7 model with respect to Recall evolution curve over the target classes.

Furthermore, the developed model is capable of detecting the most encountered targets in real-time. The model has average inference of 27.5 ms, 1.1 ms for Non Max Supression (NMS) process and an ability to infer images in 0.002 seconds per image. Additionally, the FPS metric also determines the capacity of the model to process a set of images per second, which is dependent on the model's performance. Considering that the model is tested on 1179 images, it reaches a frame rate of 42, 8 FPS. This model represents the optimal performance speed compromise, as well as being qualitative and quantitative. Additionally, the model’s performance was evaluated using unseen images containing airborne targets that were barely visible to the human eye under complex conditions, mainly due to the altitudes and distances with respect to the observer.

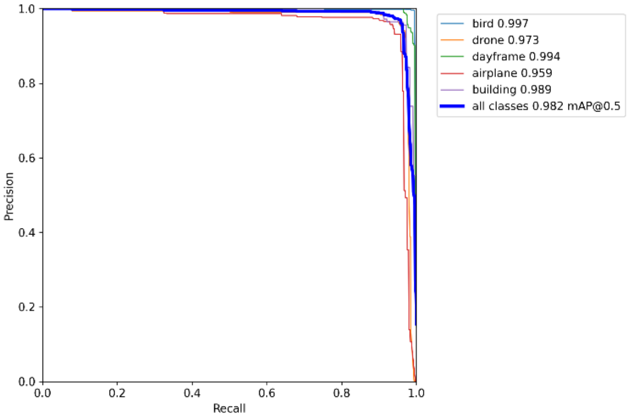


Fig. 5. Evolution of the performance of Yolov7 model with respect to F1 evolution curve over the target classes.

In view of the provided results, we confirm that our proposed model has the high inference time and the best precision, recall mAP@50 and mAP@50–95, thus outperforming the other models proposed in the literature.

Additionally, we have used performance and speed

Evaluation metrics that is suitable for our requirements and constraints to assess effectively the tested models during the development of our final Yolov7 model.

B. *DeepSort Tracking Results*

Using the selected model Yolov7, we have performed the tracking on different videos to assess the tracking ability. As part of the current study, Deepsort is used to track airborne targets for anti-drone deployment. It uses the patterns learned from the pre-trained Yolov7 detection model and later combines that with temporal information to predict associated targets' trajectories. The system keeps track of all objects by mapping their unique identifiers [21]. We have deployed the DeepSort on real-time videos that contain drones in different contexts, environments and times of the day to assess its ability to keep the target within the field of view. Fig. 8(a) and Fig. 8(b) represents a selection the tracking deployed on real-time video sequences. It is shown that model efficiently identifies and tracks the airborne targets, mainly drones and dayframes presents in the videos.

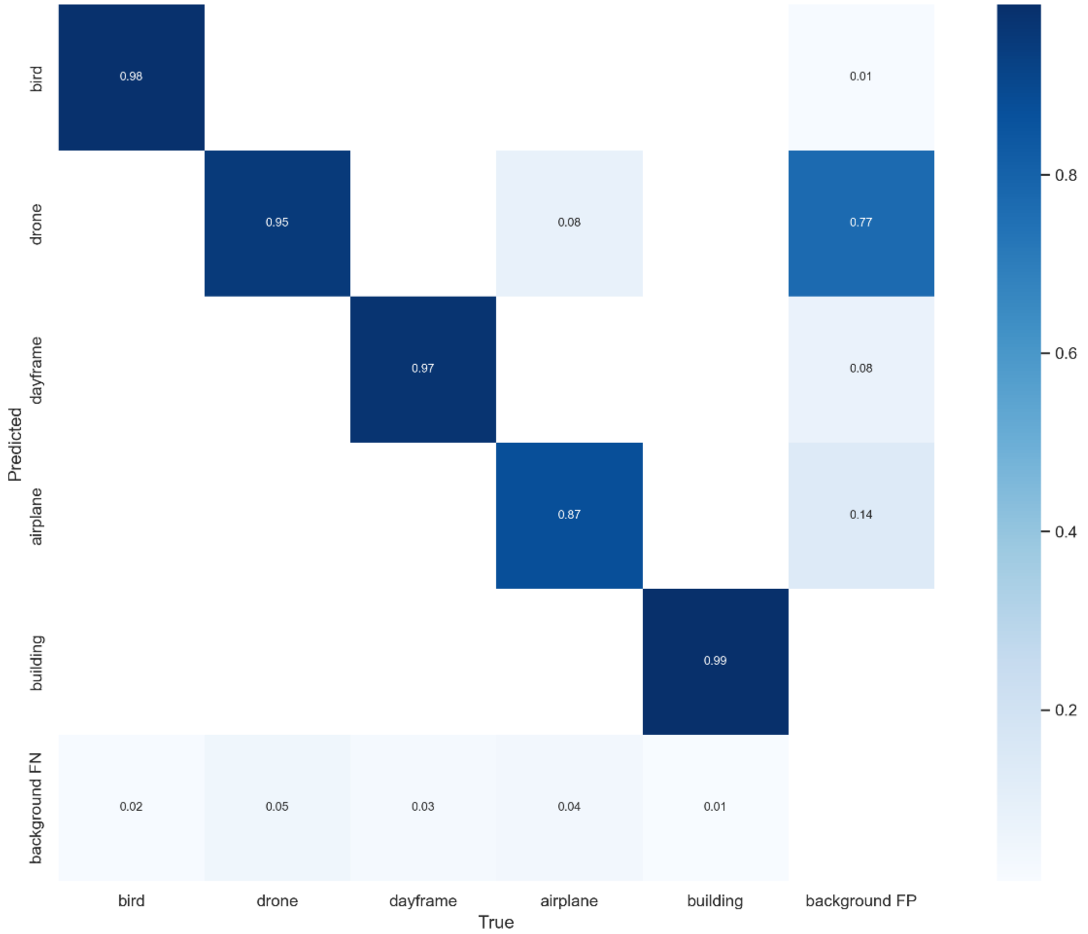


Fig. 6. Confusion matrix.

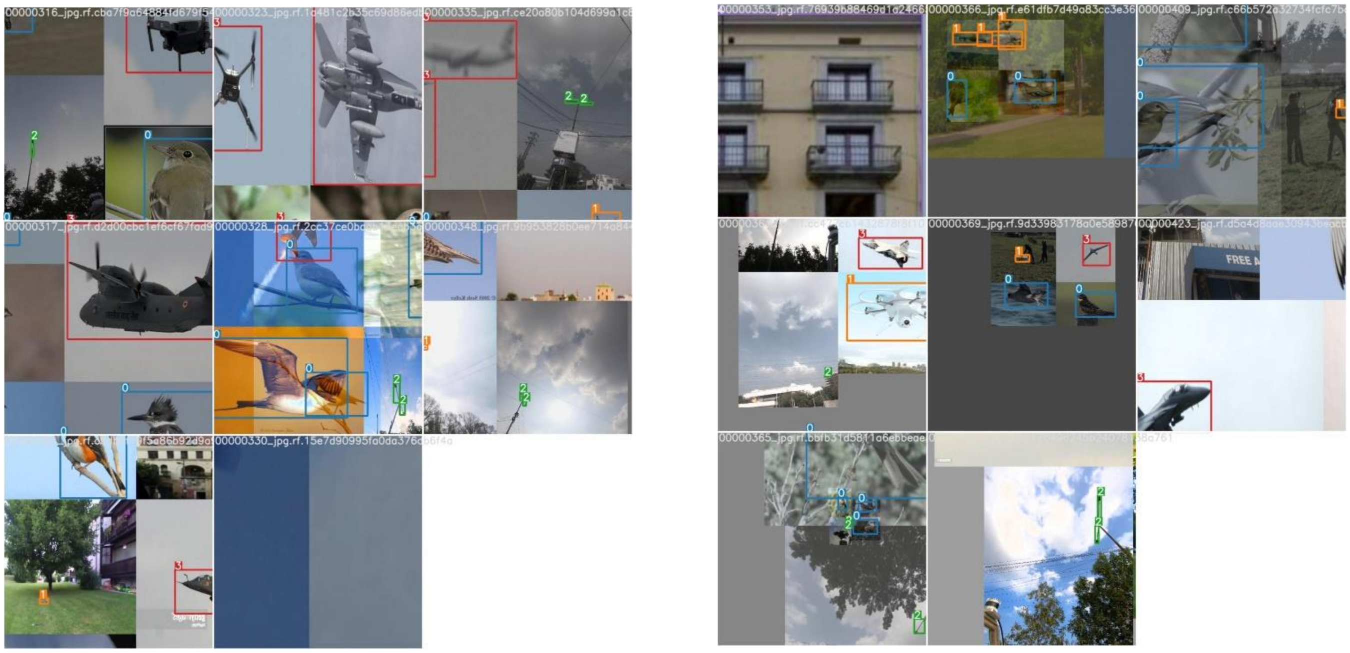
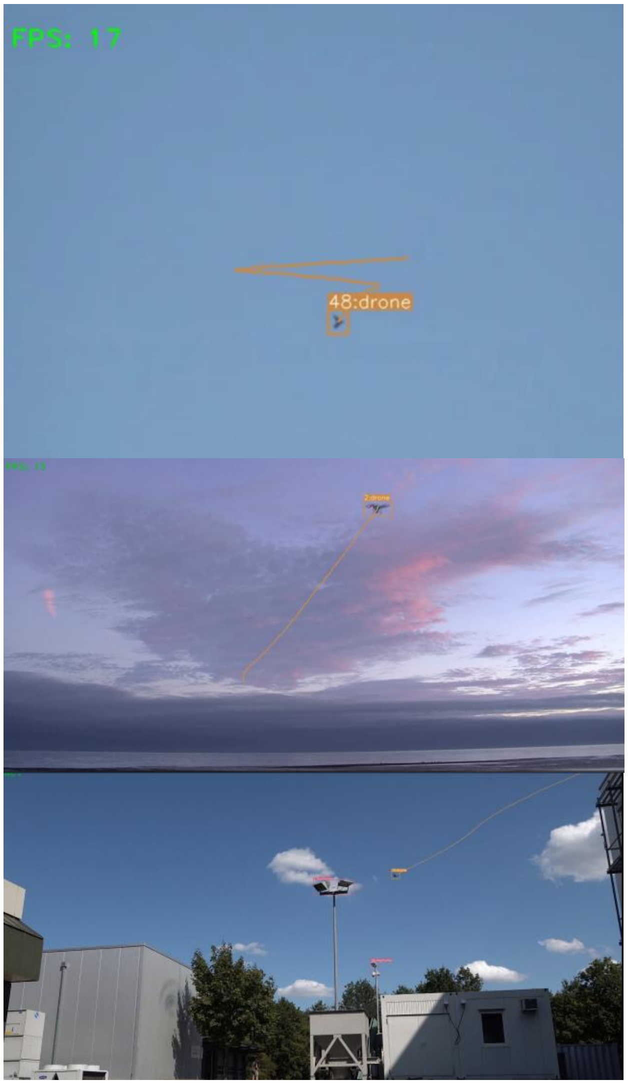
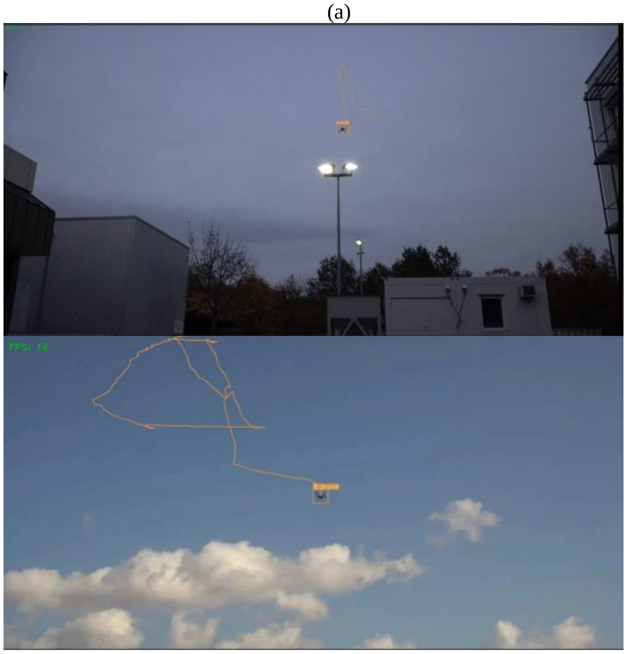
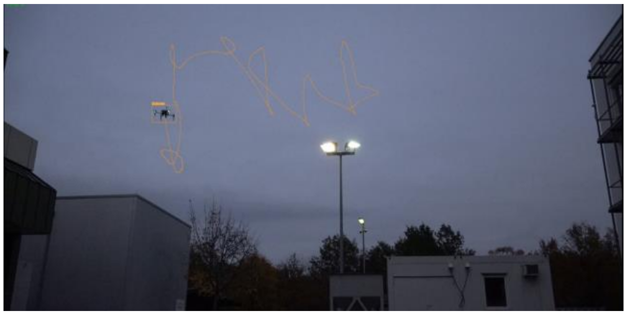


Fig. 7. Detection results of Yolov7 model.



(a)





(b)

Fig. 8. (a) Captures from the tracking on different video sequences, (b) Captures from the tracking on different video sequences.

We demonstrate the efficacy of DeepSort in our experiments in tandem with the pre-trained YOLOv7 model for tracking the selected airborne targets. With robust tracking accuracy across diverse scenarios and ability to handle challenges such as target occlusions and rapid movements, the integrated system demonstrated the ability to perform effectively in challenging scenarios.

In comparison with the state-of-of the-art papers [8], [9], [10], [11], [12] , the proposed tracking approach outperforms the other proposed models based on the ability of our model to detect and identify five airborne targets using a varied and diversified dataset and also the high tracking performance to track the detected targets while generating bounding box around it and drawing its motion line across the successive frames. Further, the proposed model is able to detect, identify and track multi-airborne targets at different views, capture angles and environment which enhance significantly the overall performance. Therefore, the proposed DeepSort algorithm with Yolov7 provides the best compromise between the performance and speed and thus satisfying the anti-drone requirements and challenges.

V. Conclusion and Perspectives

Detecting and tracking airborne targets represent important task for the effectiveness of an anti-drone process. Our paper presents a real-time model for identifying and tracking common airborne targets. Based on experimental results, the models have 42.8 FPS detection speed, 0.957 recall, 0.973 precision, 0.732, 0.982 map@0.50–0.95 and 0.753 map@0.50–0.95. In comparison with various benchmark instances recently published in the literature, the proposed model provides a high detection rate and fast inference times. Therefore, the combination of DeepSort algorithm and Yolov7 model provides high detection and tracking performance tested on real-time videos. The conducted experiments showed satisfactory results since the targets are detected and tracked rapidly and effectively across the successive frames of the videos. It suggests potential enhancements and future research directions to improve the algorithm's efficacy. In future work, we are going to collect a larger video dataset including also airplanes, and birds in the same sequences to improve further the tracking process.

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Towards High Quality PCB Defect Detection Leveraging State-of-the-Art Hybrid Models

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***Abstract*—The automatic detection of defects in printed circuit boards (PCBs) is a critical step in ensuring the reliability of electronic devices. This paper introduces a novel approach for PCB defect detection. It incorporates a state-of-the-art hybrid architecture that leverages both convolutional neural networks (CNNs) and transformer-based models. Our model comprises three main components: a Backbone for feature extraction, a Neck for feature map refinement, and a Head for defect prediction. The Backbone utilizes ResNet and Bottleneck Transformer blocks, which are proficient at highlighting small defect features and overcoming the shortcomings of previous models. The Neck module, designed with Ghost Convolution, refines feature maps. It reduces computational demands while preserving the quality of feature representation. This module also facilitates the integration of multi-scale features, essential for accurately detecting a wide range of defect sizes. The Head employs a Fully Convolutional One-stage detection approach, allowing for the prediction process to proceed without reliance on predefined anchors. Within the Head, we incorporate the Wise-IoU loss to refine bounding box regression. This optimizes the model's focus on high-overlap regions and mitigates the influence of outlier samples. Comprehensive experiments on standard PCB datasets validate the effectiveness of our proposed method. The results show significant improvements over existing techniques, particularly in the detection of small and subtle defects.**

Keywords—PCB defect detection; hybrid neural network; bottleneck transformer; ghost convolution; wise-IoU loss

I. INTRODUCTION

PCBs are the cornerstone of modern electronics, providing a critical framework for the interconnection of electronic components. They consist of a complex network of conductive pathways, tracks, and traces etched onto a non-conductive substrate, enabling the integration of various components such as resistors, capacitors, and integrated circuits to form functional electronic devices. The integrity of these boards is paramount, as any defects can lead to malfunctioning or failure of the electronic equipment. PCB defect detection, therefore, is a vital process in the manufacturing industry, aimed at identifying and rectifying flaws such as short circuits, open circuits, missing components, or misalignments. Traditionally performed by human inspectors, this process has increasingly been entrusted to automated systems that leverage advanced imaging technologies and machine learning algorithms. These systems offer greater accuracy, consistency, and efficiency in detecting a wide array of subtle and overt flaws that might be overlooked by the human eye, ensuring high-quality outputs in the fast-paced production environments that define today's electronic manufacturing sector.

Traditional image processing techniques for PCB defect detection typically involve a sequence of algorithmic steps such as noise reduction, thresholding, edge detection, and pattern recognition to analyze images of PCBs for anomalies. These methods often start with pre-processing to enhance image quality, followed by segmentation to isolate regions of interest. Techniques like morphological operations may be used to highlight features of defects, and template matching could be employed to compare segments against known good patterns. While these techniques are deterministic and relatively straightforward to implement, they come with significant shortcomings. They tend to be highly sensitive to variations in lighting, alignment, and image quality, leading to false positives or negatives. Additionally, traditional methods may struggle with the complexity of modern PCBs, which can have intricate designs and high component densities. These methods can also be computationally intensive and inflexible, requiring manual tuning and adjustments when dealing with different types of PCBs or new defect profiles, limiting their scalability and adaptability in fast-evolving manufacturing environments.

In recent years, deep learning has revolutionized the field of artificial intelligence, leading to significant advancements in various domains such as computer vision, natural language processing, autonomous vehicles, and medical diagnostics [1, 2]. At its core, deep learning utilizes neural networks with multiple layers to learn representations of data with multiple levels of abstraction, enabling the discovery of intricate structures in large datasets. As a result, applications that were once thought to be challenging, like image and speech recognition, have seen substantial improvements in accuracy and efficiency. Leveraging these developments, deep learning has also been proposed for PCB defect detection, representing a paradigm shift from traditional image processing techniques. Unlike conventional methods, which rely on hand-engineered features and are prone to performance degradation under variations in lighting and complex patterns, deep learning models can automatically learn to identify defects from data. These models, particularly convolutional neural networks (CNNs), have shown remarkable success in detecting intricate and subtle anomalies on PCBs by learning features directly from the raw pixels. However, despite their success, current deep learning methods for PCB defect detection still face challenges. They require large annotated datasets to learn effectively, which can be expensive and time-consuming to create. Moreover, they may not generalize well across different

PCB designs or manufacturing processes without extensive retraining or fine-tuning. To address these shortcomings, the method proposed in this paper integrates advanced neural network architectures that enhance feature extraction and defect localization capabilities, while also employing data augmentation and specialized loss functions to improve model robustness and generalizability. This approach aims to overcome the limitations of both traditional image processing and current deep learning techniques, providing a more reliable and adaptable solution for PCB defect detection.

The rest of the paper is organized as follows: Section II presents related studies; Section III details the proposed model; Section IV describes the experiments and results; Section V provides the conclusions.

II. Related Work

The emergence of end-to-end deep learning technology [3, 4] has introduced new opportunities for PCB fault detection. Currently, extensive research is being carried out on PCB defect detection methods that leverage deep learning. Mingu et al. [5] presented a novel contactless inspection method that utilizes deep learning to analyze thermal images for the detection of PCBA defects. The authors explore the efficacy of combining a rule-based object detection approach, employing a structural similarity index map, with advanced deep learning techniques including CNNs, region with CNN features, and autoencoders, thereby enhancing the accuracy and reliability of contactless PCBA inspection methods. Sik-Ho et al. [6] introduced PCBMTL, multitask learning model designed to concurrently tackle classification and segmentation tasks, specifically tailored for scenarios with limited data availability. This model leverages the intrinsic correlation between segmentation knowledge and classification tasks, significantly enhancing the classification accuracy even when only a sparse dataset is available. Gor et al. [7] proposed an Automated Visual Inspection (AVI) methodology for detecting hardware trojans (HTs) on PCBs, utilizing imagery from a low-cost digital optical camera. This method combines traditional computer vision techniques with a dual-tower Siamese Neural Network (SNN), structured within a three-stage pipeline for effective HT detection. To address the issues of inadequate accuracy and speed in visual matching systems, the study in [8] introduced a deep learning-based alignment system utilizing YOLOv5. This system enhances production efficiency by preprocessing images captured by an industrial camera, delineating sensitive areas rich in feature points for improved alignment accuracy. Naifu et al. [9] employed techniques such as relative position estimation, spatially adjacent similarity, and k-means clustering of patches to discern finely classified semantic features, followed by a local image patch completion network that learns the feature consistency between these local patches and the background, using the disparities between the estimated and original image patches to effectively identify anomaly areas in PCBs.

To enhance the efficiency of current defect detection algorithms, [10] introduced RAR-SSD, a novel method combining multiscale PCB defect target detection with an attention mechanism. This approach integrates a lightweight receptive field block module (RFB-s) with an attention mechanism, effectively focusing on crucial features across various channels without escalating computational demands, and incorporates a feature fusion module that synergizes low-level and high-level feature information, resulting in a comprehensive feature map that significantly boosts fault recognition accuracy. JiaYou et al. [11] introduce an advanced deep learning network specifically designed to tackle the challenge of detecting small or variable defects on PCBs in real-time. The proposed improvements include a unique multi-scale feature pyramid network that boosts tiny defect detection by incorporating context information and a refined complete intersection over union loss function that accurately targets and identifies these minuscule defects. CS-ResNet [12] introduced a new model, which innovates upon the standard ResNet by incorporating a cost-sensitive adjustment layer. This model specifically addresses class imbalance by assigning greater weights to minority real defects based on their degree of imbalance, and optimizes performance through the minimization of a weighted cross-entropy loss function. Boyuan et al. [13] presented a cutting-edge PCB defect detection method utilizing YOLOv7. Additionally, the integration of the CBAM attention mechanism with a feature fusion module enables the model to selectively focus on pertinent feature channels and spatial locations, significantly boosting the discriminative power of the feature representation and thereby increasing overall accuracy. KD-LightNet [14] introduced an efficient and lightweight defect detection network optimized for edge computing scenarios. The network architecture, LightNet, is crafted using structure reparameterization to boost feature extraction capabilities while reducing model complexity.

III. Method

In this section, we provide details of our approach for PCB defect detection. Fig. 1 illustrates the overall structure of the proposed model, which includes three modules: Backbone for extracting features from the input image, Neck for enhancing the feature maps, and Head for making predictions. Initially, the input image is processed by the Backbone, consisting of multiple layers that perform feature extraction. Subsequently, the extracted features are refined by the Neck module, which is designed to enhance and integrate the feature maps at different scales. Finally, the Head module takes over, comprising three key components: Classification, Center-ness, and Regression, which work collectively to output the final defect detection results. Details of each module will be explained in the following subsections.

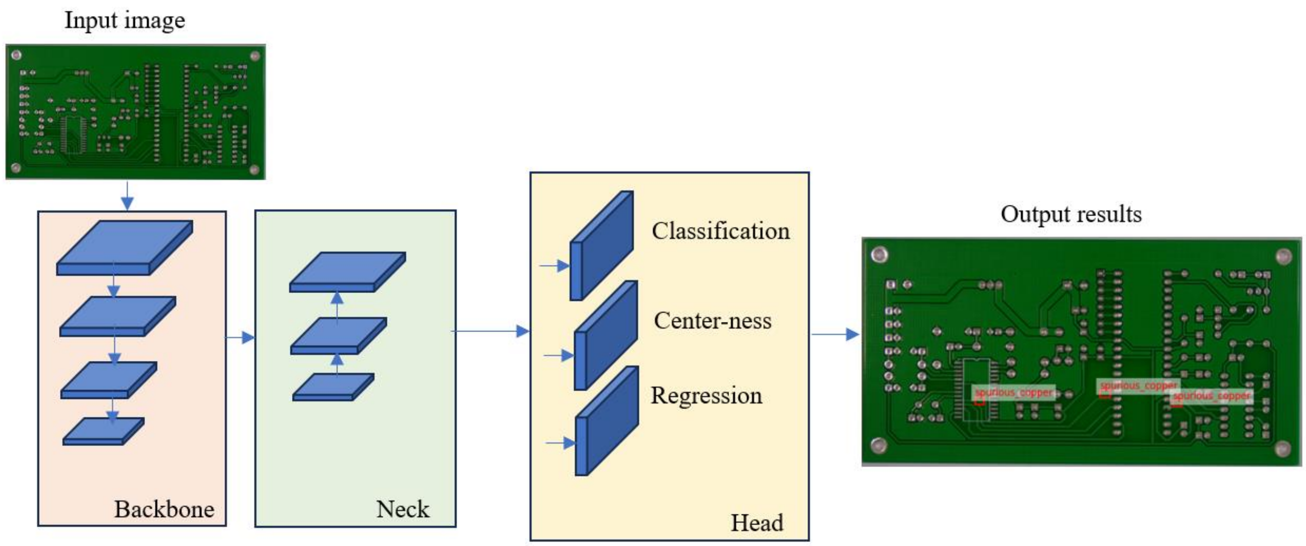

Fig. 1. Overall structure of the proposed model.

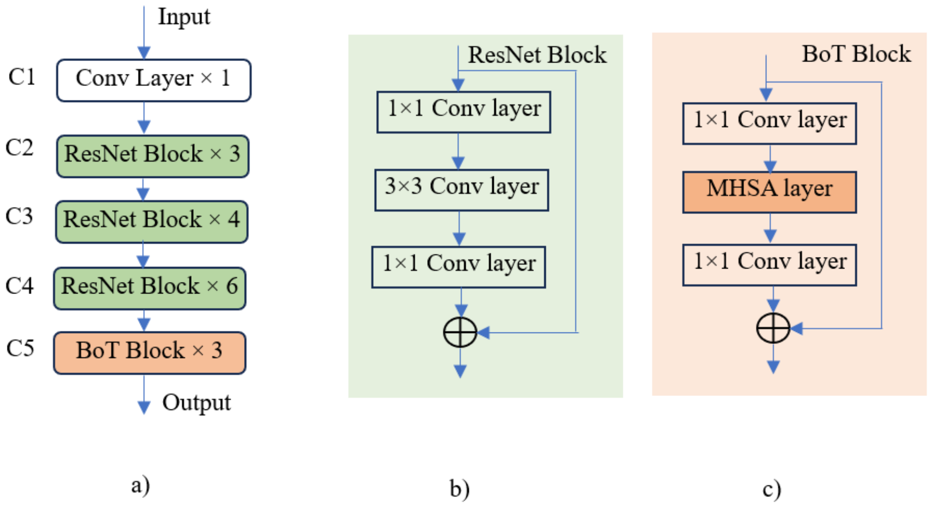

Fig. 2. The structure of the feature extraction network (a) which includes input (b) ResNet Block (c) BoT block.

A. *Feature Extraction with Self-Attention Mechanism*

1) The backbone network proposed for PCB defect detection is a critical component of the object detection system, designed to process input images and extract relevant features that are essential for identifying defects. The advanced architecture of this backbone is built upon a combination of convolutional layers and ResNet blocks [15], further enhanced with Bottleneck Transformer (BoT) blocks [16]. The structure is outlined in Fig. 2, which depicts the sequential layers and blocks within the network. In detail, the backbone begins with a single convolutional layer (C1) that performs initial feature extraction. This is followed by a series of ResNet blocks (C2, C3, C4) that apply residual learning to prevent the vanishing gradient problem and allow deeper networks to learn effectively. Each ResNet block consists of a bottleneck design with three convolutional layers: a 1×1 convolution that reduces the dimensionality, a 3×3 convolution that processes features, and another 1×1 convolution that restores dimensionality. These blocks are equipped with skip connections that add the input of the block to its output, facilitating the training of deep networks by allowing gradients to flow through.

2) The novelty of this architecture lies in the integration of BoT blocks (C5), which introduce a multi-head self-attention (MHSA) mechanism within the transformer architecture [17]. Each BoT block is comprised of a 1×1 convolution layer followed by an MHSA layer and another 1×1 convolution layer. The MHSA layer enables the network to focus on different parts of the image when extracting features, which is particularly beneficial for detecting small objects-a common challenge in PCB defect detection. This capability is contrasted with the DETR (Detection Transformer) model [3], which shows improvements in detecting larger objects but not smaller ones. The use of BoT blocks in the backbone could potentially address this shortfall, enhancing the model's ability to recognize smaller defects on PCBs that are often difficult to detect. In the BoT block, the MHSA mechanism efficiently captures long-range dependencies across the input feature map. By utilizing multiple attention heads, MHSA is able to concurrently process and focus on various aspects of the semantic space within the feature map. This allows the model to consider information from different representation subspaces at reduced computational costs. The operation of MHSA is as follows:

$$MHSA(Q,K,V) = Concatenation(H^0,H^1,H^2,H^3) \quad (1)$$

where, Q, K, and V represent three linear layers used for computing queries, keys, and values in a standard self-attention task. H^i represent the head of the self-attention mechanism as follows:

$$H^i = Softmax(Q_iK_i^T + qr^T) \times V_i, i \in [0,3] \quad (2)$$

$$qr = (R_h + R_w) \times Q \quad (3)$$

where, R_h ans R_w represent height and width relative position, respectively.

B. Improving Multi-scale Feature with Ghost Convolution

The neck network for PCB defect detection is designed based on Ghost Convolution [18], as depicted in Fig. 3. This network serves as an intermediary between the feature-rich output from the backbone and the predictive head of the model, enhancing the feature maps for more accurate defect localization. Starting from the deepest layer (C5), the network utilizes Ghost Convolution layers, which are designed to generate more feature maps from fewer intrinsic maps, thereby reducing computational requirements while maintaining effective representation capacity. This is followed by an upsampling step, which increases the resolution of the feature maps to match the scale of the subsequent layer. The upscaled features are then concatenated with the features from the previous layer (C4), integrating multi-level semantic information. This process is repeated as the network proceeds to shallower layers (C4 to C3). Each time, the Ghost Convolution layers generate rich feature representations that are then upsampled and concatenated with features from earlier in the network. This concatenation ensures that the final feature maps encompass both high-level semantic information and finer, low-level details, which is crucial for detecting the often-minute anomalies present in PCBs. The repeated pattern of Ghost Convolution, upsampling, and concatenation progressively enriches the feature maps, culminating in a comprehensive composite that feeds into the detection head. The head then uses these refined features to make precise predictions about the presence, location, and types of defects on the PCB. This neck architecture, with its efficient and hierarchical processing, is particularly well-suited for the demands of PCB defect detection, where the ability to discern subtle and small-scale imperfections is key.

1) Ghost convolution: Ghost Convolution is an innovative approach to convolutional neural network design that aims to reduce computational workload and model complexity without sacrificing performance. The core idea behind Ghost Convolution is to generate additional feature maps, known as "ghost" features, from inexpensive operations on the original convolutional features. This is achieved by applying a series of linear transformations, such as simple arithmetic operations or small-kernel convolutions, to the output of standard convolutional layers. The original set of feature maps is obtained through regular convolution operations, which can be computationally intensive. Then, for each of these original maps, several ghost feature maps are derived using the lightweight transformations. These ghost maps are capable of capturing variations and fine details by reusing the information present in the original feature maps, effectively augmenting the feature space with minimal extra computation. This process substantially reduces the number of direct convolutions that the network needs to perform, thus decreasing the number of parameters and the computational cost. Despite this reduction, Ghost Convolution preserves the network's capacity to encode rich and complex representations of the input data, making it particularly useful for resource-constrained environments or applications where efficiency is paramount, such as mobile devices, embedded systems, or real-time applications.

For a standard convolution, the number of FLOPs is calculated as follows:

$$\text{FLOPs}_{Standard} = H_{out} \times W_{out} \times N_{out} \times (C_{in} \times K_h \times K_w + 1) \quad (4)$$

where, H_{out} and W_{out} are the height and width of the output feature map; N_{out} is the number of output channels; C_{in} is the number of input channels; K_h and K_w are the height and width of the kernel.

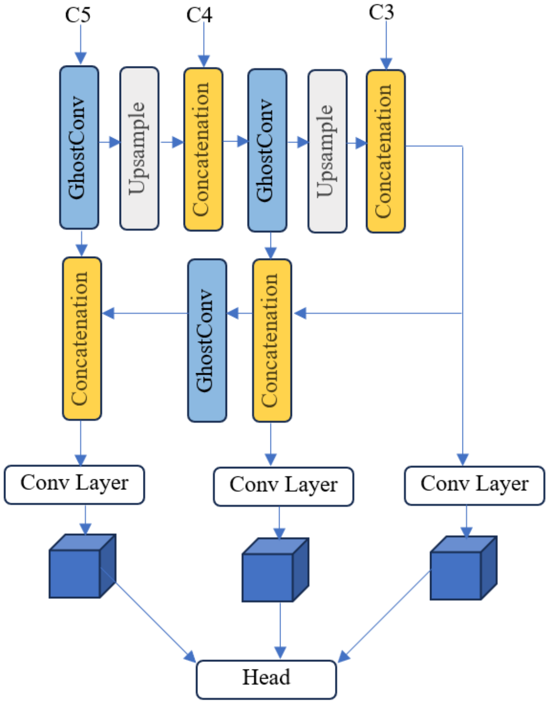

Fig. 3. The neck network with ghost convolution layers.

For Ghost convolution, we first calculate the FLOPs for the initial standard convolution that generates the intrinsic feature maps, and then add the FLOPs for the linear operations used to generate the ghost feature maps. The equation for Ghost convolution is:

$$\text{FLOPs}_{Ghost} = H_{out} \times W_{out} \times N_{int} \times (C_{in} \times K_h \times K_w + 1) + H_{out} \times W_{out} \times N_{ghost} \times \left(N_{int} \times K_{hghost} \times K_{wghost} + 1\right) \tag{5}$$

where, N_{int} is the number of intrinsic output channels produced by the initial standard convolution; N_{ghost} is the number of ghost channels generated per intrinsic channel; K_{hghost} and K_{wghost} are the height and width of the kernel for generating the ghost feature maps, which are typically much smaller than the original convolution kernel size.

The term $N_{int} \times (C_{in} \times K_h \times K_w + 1)$ calculates the FLOPs for the initial convolution, and the term $N_{ghost} \times \left(N_{int} \times K_{hghost} \times K_{wghost} + 1\right)$ calculates the FLOPs for generating the ghost feature maps. Typically, N_{int} is much less than N_{out} and the kernel size for ghost operations (K_{hghost}, K_{wghost}) is smaller, leading to a significant reduction in FLOPs compared to standard convolution.

C. Detection Head with Wise-IoU Loss

1) We employ FCOS head [19] on each output feature layer. FCOS divides its detection head into three branches: the classification branch, the bounding box regression branch, and the centerness branch. In classification branch, a Focal Loss [20] is used to address class imbalance by reducing the weight of easy negatives. The centerness branch uses a binary cross-entropy loss that guides the model to predict higher centerness values for locations closer to the center of an object. For the bounding box regression branch, Wise-IoU loss [21] is employed. This is a novel loss function that modulates the geometric penalty based on the overlap between the predicted bounding box and the ground truth. If the overlap is high, the penalty is reduced, which helps the model to better refine boxes that are already largely accurate. The Wise-IoU loss also includes an outlier penalty term that increases the loss for poor predictions, preventing the model from being overly influenced by difficult or mislabeled examples. The formula for the Wise-IoU loss function is shown as follows:

$$L_{Wise-IoU} = r \times L_{IoU} \times exp(\frac{\left(x-x_{gt}\right)^2 + (y-y_{gt})^2}{(W_g^2 + H_g^2)}) \tag{6}$$

where, r represents the gradient gain.

2) The Wise-IoU loss specifically enhances the bounding box regression branch by incorporating a distance attention mechanism that scales the loss based on the distance metric between the anchor and the target frame. This scaling ensures that when the predicted box is already close to the ground truth (high IoU), the model is encouraged to make finer adjustments rather than over-penalizing small discrepancies. Moreover, by introducing a gradient attenuation factor for outliers, the Wise-IoU loss ensures that samples with poor quality predictions do not dominate the gradient update during backpropagation, thus stabilizing training and steering the model away from local optima that are not generalizable. This thoughtful design of the loss function supports more precise localization in PCB defect detection, which is critical for ensuring the accurate identification of defects.

IV. Experiments

A. Dataset and Experimental Setup

The dataset utilized in this study is derived from the PCB defect dataset released by the Intelligent Robotics Open Laboratory at Peking University. It encompasses various types of defects, such as shorts, open circuits, spurs, spurious copper, mouse bites, and missing holes. To mitigate the risk of network overfitting, we augmented the original 693 samples using techniques like random rotations, random cropping, brightness adjustments, and noise injection, resulting in a substantial increase to 5,814 samples. The distribution of different defect types is depicted in Fig. 4. We partitioned the expanded dataset into training, validation, and test sets in a ratio of 6:2:2, respectively.

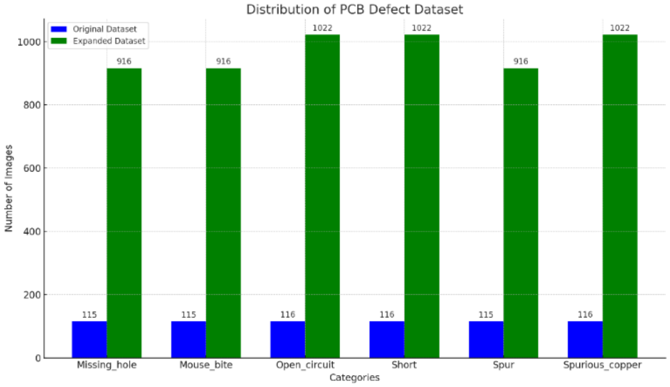

Fig. 4. Distribution of PCB defect dataset.

We conducted our training and evaluation on a high-performance Windows PC outfitted with an Intel Core i7-10400 CPU, an NVIDIA GeForce RTX 4080 GPU, and 32GB of RAM, ensuring efficient processing capabilities for deep learning tasks. Our software stack consisted of Python 3.8, leveraging libraries such as OpenCV for image processing and PyTorch for model development and training. The models were trained over 300 epochs with a batch size of 2, and we standardized the input image size to 640×640 pixels to maintain consistency in training and testing.

For model evaluation, we adopted two primary metrics: the mean average precision (mAP) and the detection speed, measured in frames per second (FPS). The mAP provides a comprehensive measure of model accuracy across all classes, factoring in both precision and recall, while FPS gauges the model's real-time performance capabilities. These benchmarks allowed us to assess the overall effectiveness and efficiency of our PCB defect detection models in a controlled and quantifiable manner.

B. Comparison with other Models

Table I provides a comparative analysis of various object detection models on the PCB defect dataset, showcasing their performance in terms of mean average precision (mAP), frames per second (FPS), and computational complexity measured in GFLOPs. The proposed model outperforms all other models with an exceptional mAP of 99.2%, indicating its superior accuracy in defect detection. Despite this high precision, it maintains a competitive detection speed of 51 FPS, balancing efficiency with effectiveness. Notably, the proposed model achieves this while having a lower computational cost (41.0 GFLOPs) than YOLOv5 and Faster R-CNN, which have higher GFLOPs of 100 and 170, respectively. The YOLOv7 and the Improved YOLOv5 models also exhibit high mAP scores, suggesting that the latest iterations and enhancements in the YOLO series continue to advance the state-of-the-art in object detection. However, the proposed model's edge in mAP suggests that the integration of novel architectural features or training strategies could be particularly beneficial for the specific challenges presented by PCB defect detection. The Transformer-YOLO and the Improved YOLOv5, while yielding high accuracy, do not report FPS, which leaves a gap in understanding their real-time applicability. On the other end of the spectrum, SSD demonstrates the lowest GFLOPs, indicating a very efficient model, but it lags in mAP, underscoring a trade-off between computational efficiency and detection accuracy. Overall, the results in Table I highlight the proposed model's capability to set a new benchmark for PCB defect detection by achieving a harmonious balance between accuracy, speed, and computational efficiency.

Fig. 5 presents a comprehensive visualization of the detection results achieved by the proposed PCB defect detection model. Across multiple instances, the model successfully identifies and localizes various types of PCB defects. Each type of defect is accurately marked with bounding boxes and labeled, indicating a high level of precision in the model's predictive capability. The clarity of the bounding boxes and the accuracy of the labels suggest that the model is well-tuned to the intricacies of PCB defect detection. The absence of mislabeling or missed detections in the provided visualization underscores the robustness of the model and its potential for practical applications in quality control and automated inspection systems within electronic manufacturing.

TABLE I. COMPARING THE PROPOSED MODEL WITH OTHER MODELS ON THE PCB DEFECT DATASET

Models	mAP (%)	FPS	GFLOPs
Faster R-CNN [22]	74.4	21	170
SSD [23]	82.2	42	2.5
YOLOv3 [24]	87.2	69	65
YOLOv5	91.4	102	100
Transformer-YOLO [25]	97.0	-	-
YOLOv7 [26]	97.8	54	51.2
Improved YOLOv5 [27]	97.9	-	53.5
Proposed Model	99.2	51	41.0

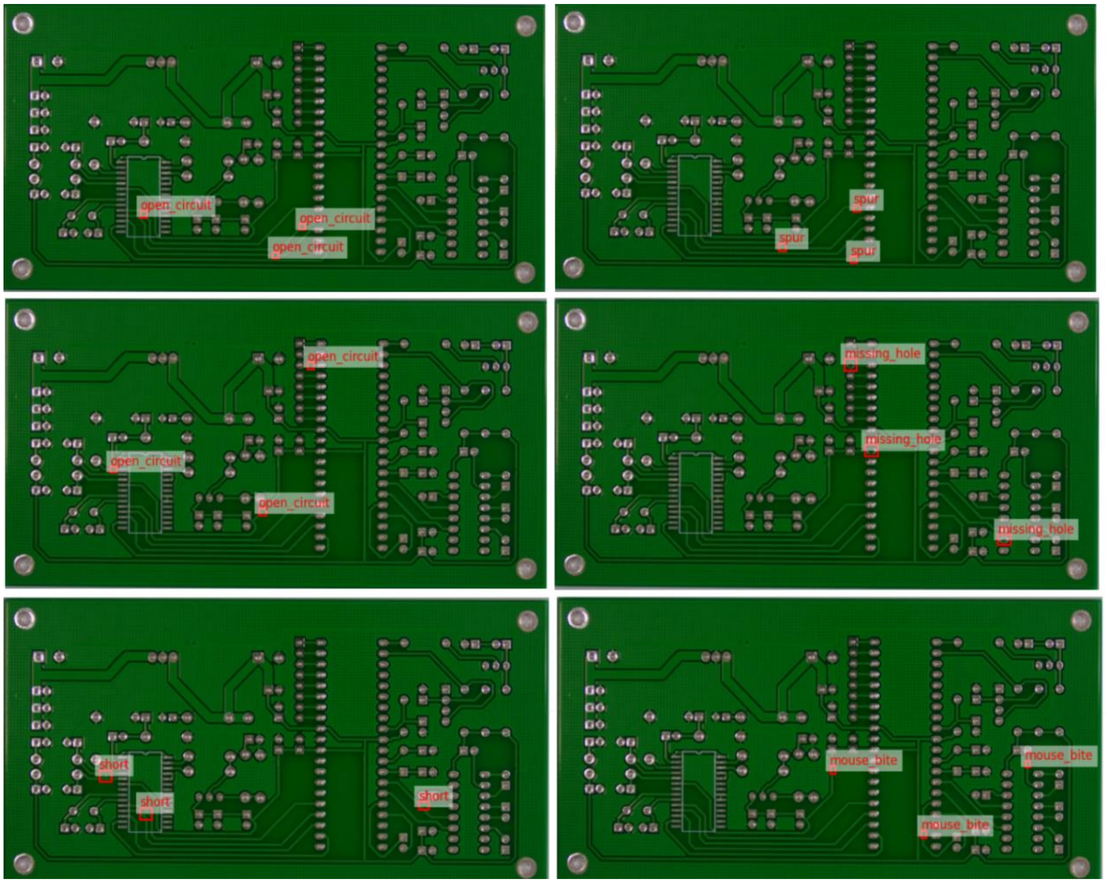

Fig. 5. Visualization of detection results of the proposed model.

C. Effect of Backbone with Self-Attention Mechanism

We also conduct experiments on the PCB defect validation set with various backbone architectures to evaluate the effectiveness of the proposed backbone with self-attention mechanism. Fig. 6 illustrates the performance trade-offs between mean average precision (mAP) and inference speed (FPS) for various backbone architectures on the validation set, including ResNet-50, ResNet-101 [15], EfficientNet [28], SENet-50 [29]. The proposed model achieves the highest mAP of 98.4% with a competitive FPS of 51, showcasing its superior defect detection accuracy without significantly compromising on speed. The ResNet-50 and ResNet-101 architectures offer a good balance between accuracy and speed, with ResNet-101 slightly trailing in FPS at 41 but offering near-top mAP performance at 98.2%. Notably, EfficientNet stands out with the highest FPS of 68, suggesting it is the fastest model; however, this speed comes at the cost of a lower mAP of 95.8%. SENet-50 has the lowest mAP of 94.4% and a modest FPS of 48, indicating it may not be the optimal choice for scenarios where high precision is critical. Overall, the proposed model’s impressive mAP, coupled with a substantial FPS, positions it as a compelling choice for real-time PCB defect detection applications.

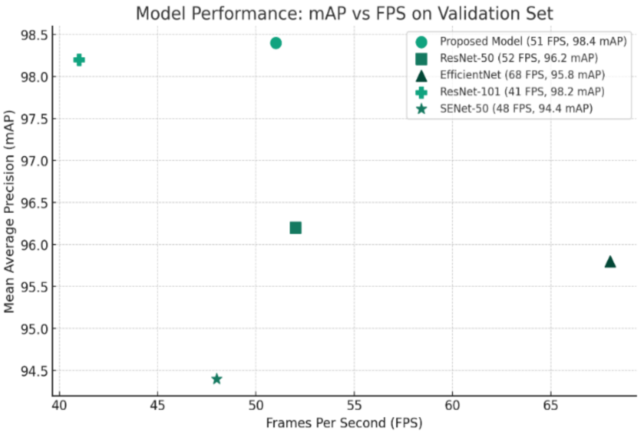

Fig. 6. The performance trade-offs between mean average precision (mAP) and inference speed (FPS) for various backbone architectures on the validation set.

V. Conclusions

In conclusion, this research paper proposes a novel approach to PCB defect detection, leveraging advanced hybrid neural network architecture. Our model integrates a ResNet and Bottleneck Transformer Backbone, a Ghost Convolution Neck, and Fully Convolutional One-stage detection Head, showing superior performance in identifying subtle and small-scale defects on PCBs. The comparative analysis highlights our model's exceptional mean average precision of 99.2%, significantly surpassing that of existing object detection models. Moreover, it achieves this high level of accuracy while maintaining a competitive detection speed of 51 FPS and requiring fewer computational resources compared to other high-performing models. The introduction of extensive augmentation techniques has further enhanced the dataset's diversity, improving the model's robustness and its ability to generalize across various PCB defect types. Future work will focus on optimizing the model to further improve its detection capabilities, particularly for the smallest and most challenging defects. Additionally, we will explore the potential for real-time processing in greater depth, aiming to extend the model's applicability to industrial settings and automated quality control systems. The success of this study marks a significant step forward in the field of automated defect detection, promising to enhance the reliability and efficiency of electronic manufacturing processes through the adoption of advanced neural network architectures.

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Advancing Parkinson's Disease Severity Prediction using Multimodal Convolutional Recursive Deep Belief Networks

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***Abstract*—Parkinson's disease (PD), a progressive neurological ailment predominantly affecting individuals over the age of 60, involves the gradual loss of dopamine-producing neurons. The challenges associated with the subjectivity, resource intensity, and limited efficacy of current diagnostic methods, including the Unified Parkinson's Disease Rating Scale (UPDRS), neuroimaging, and genetic analysis, underscore the need for innovative approaches. This paper introduces a groundbreaking multimodal deep learning framework that integrates Recurrent Neural Networks (RNN-DBN) for precise feature selection and Convolutional Neural Networks (CNNs) for robust feature extraction, aiming to enhance the accuracy of PD severity prediction. The methodology synergistically incorporates genetic data, imaging data from MRI and PET scans, and clinical evaluations. CNNs effectively capture spatial and temporal patterns within each data modality, preserving inter-modal linkages. The proposed RNN-DBN architecture, by skillfully leveraging temporal dependencies, improves model interpretability and provides a clearer understanding of the progression of Parkinson's disease symptoms. Evaluation across diverse PD datasets demonstrates superior predictive performance compared to existing methods. This multimodal deep learning framework holds the potential to revolutionize PD diagnosis and monitoring, offering physicians a valuable tool for assessing the condition's severity. The integration of various data sources enhances the model's accuracy, providing a holistic perspective on Parkinson's disease progression. This, in turn, facilitates improved clinical decision-making and patient care. Notably, the implementation in Python achieves a remarkable accuracy of 94.87%, surpassing existing methods like EOFSC and CNN by 1.44%.**

Keywords*—Parkinson's Disease (PD); Convolutional Neural Networks (CNN); Deep Belief Networks (DBN); Rat Swarm Optimization (RSO)

I. Introduction

Parkinson's disorder is a persistent, innovative neurodegenerative condition marked by a gradual degeneration of dopamine-producing brain cells. This causes both non-motor symptoms like mental deterioration and anxiety and depression in addition to physical signs like shaking hands, a slowing of activity, and stiffness [1]. Although the precise etiology is yet unresolved, environmental and genetic variables are thought to be involved [2]. Although there doesn't exist a therapy, there are treatments available to control indications, and identification often relies on a medical exam. According to the worldwide assessment of disorders of the brain, Parkinson's illness symptoms and prevalence have quickly grown globally [3]. Parkinson's disease is often diagnosed by a doctor based on the symptoms experienced by the individual and the neurological exam that should be done following learning about the illness's background. Parkinson's syndrome may potentially be the mental health condition with the greatest global growth rate. Having the exception of an infecting origin, this pandemic-like fast increase in the number of persons with Parkinson's disease can be matched to many of the traits often seen throughout a global epidemic [4]. An organized strategy to addressing fundamental palliative care concerns is lacking. Examples include supporting relatives and healthcare supporters, paying tribute to religious health, talking about the outlook, and making plans for increasing handicap [5]. Although there seems to be a great deal of curiosity in Parkinson an assessment of gait, there is no quantitative instrument to aid doctors in gait assessment, which can help illuminate the increase in Parkinson's disease occurrence rises with age. A strong gait classification could be useful for doctors because alterations in gait are one of the disease's early signs [6](based on the UPDRS) using gait information from this medical setting [7]. According to WHO data, around 10 million individuals worldwide have been impacted by PD. Patients who don't receive early diagnosis end up with an incurable, irreversible cognitive condition. In its final stages, the illness is fatal and untreated in the majority of patients. Movement-related symptoms including a state of repose tremor where the arms and legs move erratically (diskinesya), lack of motion (bradykinesia), unstable posture (balance issues), and stiffness are the hallmarks of PD patients. Because motor signs appear when the illness is already somewhat severe, [8]. Although the precise etiology of Parkinson's disease is unknown, experts suggest a complicated interaction of biological, environmental, and personal factors is to blame [9]. The condition appears to be associated with genetic susceptibility, history in the family, and unusual abnormalities in particular genes; being subjected to some environmental chemicals, such as insecticides and toxic metals, as well as head traumas, may further raise the chance of developing it. Parkinson's disease is more frequent in elderly people and somewhat more prevalent in males, thus age and gender both play a part. Although the precise causes are yet unknown, oxidative strain, neurological inflammation, and the development of aberrant clumps of protein called

Lewy bodies in the cerebral cortex are considered to be factors in the damage to neurons observed in Parkinson's disease [10].

Given the lack of a reliable diagnostic tool for PD and the high probability of an incorrect diagnosis, particularly when performed by a non-specialist: there is a 20% chance that the medical diagnosis will be incorrect. The accuracy of a medical diagnosis can be improved by carefully examining the primary signs, including shaken hands, bradykinesia, and stiffness, although clinical decisions might be impacted by the objectivity of the doctor who is treating the patient [11]. More fundamentally, investigations that only divide patients into PD and non-PD give no benefit for raising their standard of existence [12]. Despite the demand for instruments to improve the precision of diagnostics, the determination is often made once the disease has advanced to more crippling stages, or when indications becomes apparent. Several investigators recognized this drawback and used an alternative strategy. [13]. The majority of work is being put into developing novel techniques for clinical assistance since accurate diagnoses as well as early phase detection rank highly in medical practice. These techniques could improve accuracy and reduce the amount of resources and time needed. A deep neural network for Parkinson's disease identification entails gathering an extensive collection of people regardless of the condition, performing data preprocessing and feature extraction, choosing a suitable deep neural network architecture, training and validating the model, assessing its efficacy, guaranteeing interpretability, employing it carefully in a medical information, and continuing surveillance and upkeep while following to ethical guidelines and securing the required authorization [14]. Recent breakthroughs in artificial intelligence have significantly improved the ability to recognize, categorize, and measure different trends in clinical information throughout a variety of medical sectors. Smart technology that can recognize signs of Parkinson's disease and estimate the Parkinson intensity rate. Despite risk factors from the environment for Parkinson's disease have received a lot of consideration, family histories are now more commonly understood to play an important significance in predicting the likelihood of developing the condition. Despite the fact that familial PD cases make up fewer than 10% of all cases, the discovery of numerous genetics [15] highlights the significance of early detection and treatment for superior outcomes and offers promise of enhanced therapies and potential beneficial medications in the years to come.

The Key contributions of the article are given below:

- The model makes use of a sizable and varied dataset, which is essential for capturing a wide range of disease-related patterns and enhancing generalization. Rigid data preparation is carried out to guarantee data quality before model training.
- Using data augmentation techniques further enriches the dataset, increasing its variety and enhancing the model's ability to generalize to different scenarios and patient profiles.
- The ability to divide and separate audio signals is a distinctive feature, especially relevant for Parkinson's disease diagnosis, as it can help capture vocal characteristics and tremors, which are key indicators of the disease.
- The incorporation of Rat Swarm Optimization for hyper parameter tuning is a novel approach.
- Because the specially created RNN is adapted to the properties of the dataset, it can successfully extract pertinent features from the audio signals.
- The iterative nature of the suggested technique, comprising both feature selection and hyperparameter optimization, continually refines the model's architecture. The DBN functions as an intelligent feature selector, enhancing the feature representation acquired from the RNN.

The investigative process unfolds as follows: In Section II. Related works, an extensive examination of prior research is conducted, specifically exploring prediction problems and the diverse array of optimization strategies applied in those contexts. Moving on to Section III, a detailed exploration of problem statements is undertaken. Section IV expounds upon the recommended approach or strategy to address these identified issues. Section V discusses the findings and research limitations. Section VI is dedicated to a comprehensive discussion of performance evaluation criteria and metrics. Subsequently. Finally, Section VII aids as the concluding segment of the essay, short key outcomes and insights derived from the investigation. Section VIII discusses the future work.

II. Related Work

Parkinson's disease, which is brought about by the death of dopamine-producing neurons, is the next most common degenerative illness. Parkinson's illness is still characterized by striatal dopamine production insufficiency since this brain area is devoid of its neuronal activities. These individuals exhibit a variety of motor and non-motor symptoms, according to the medical evaluation. A deep learning neural network has been used to categorize the MR images of Parkinson's disease-related individuals and healthy controls in order to better understand the structural problems in the brain caused by dopamine insufficiency in the condition. The architecture of a network of convolutional neural networks The Parkinson's disease diagnosis is improved with AlexNet. The transferred learning network trains on the MR images and then tests them to determine their correctness. Sivaranjini and Sujatha [16] suggested approach achieves an accuracy of 88.9%. In the near future, deep learning models will be able to aid physicians in determining the presence of Parkinson's disease and produce an accurate and enhanced patient category categorization. Require to determine if the predictions made by the model match the clinical diagnosis and assist in making treatment recommendations for those who do well.

Parkinson's disease is a neurological condition that develops progressively and manifests gradually, making getting diagnosed early challenging. Parkinson's disease can be identified by a neurologist after studying the individual's medical records and several scans. Additionally, by observing movements of the body, movement analyzers can detect Parkinson's disease. Modifications in language can be utilized as a quantifiable signal to diagnose Parkinson's identification, according to the latest study. Lamba et al. [17] suggest a prospective Parkinson's disease detection method that is voice signal-based hybridization. To figure out how to do that, the researchers tried a variety of selecting features methodologies and methods for classification and created a framework using the blend that performed well. Three choice of features techniques—mutual knowledge gain, additional trees, and biological algorithms—as well as three classifiers—naive bayes, k-nearest neighbors, and random forest—have been utilized to create numerous combinations. The voice data from the database of machine learning at UCI (University of California, Irvine) has been utilized to evaluate the effectiveness of various pairings. The artificial minority over sampling method (SMOTE), which takes advantage of the dataset's extreme inequalities, is used to solve the class balancing issue. The greatest result, with an accuracy rate of 95.58%, was demonstrated by combining the use of genetic algorithms and random forest classifiers. This outcome is also superior to current literature-based research. To recognize sickness sooner, numerous information should be evaluated.

Parkinson's illness is a neurological condition which develops over time and manifests gradually, making getting diagnosed early challenging. Parkinson's disease may be recognized by a neurological specialist after studying the individual's medical records and several scans. Additionally, through observing how one moves motion analyzers may identify Parkinson's disease. Modifications in language can be utilized as a quantifiable signal to diagnose Parkinson's disease identification, according to new research. Quan, Ren, and Luo [18] suggest a preliminary Parkinson's illness detection method that is speech signal-based hybridization. In order to do this, the researchers tried multiple combinations of selecting features methodologies and algorithms for classification and created the model using the combination of techniques that worked better. Three decision-making techniques mutual knowledge gain, additional trees, and evolutionary algorithms—as well as three classifiers naive bayes, k-nearest neighbors, and random forest—have been employed to create several distinct combinations. The voice dataset from the UCI (University of California, Irvine) machine learning collection is being utilized to evaluate the efficiency of various combos. The manufactured minority over sampling method (SMOTE) solves the group managing issue since the information set is substantially unbalanced. With 95.58% accuracy, the genetic code and natural forest classifier combo performed very well. Phase categorization of PD to examine its application in the classification issue with multiple labels and to increase efficiency, take into account an additional complicated DL network topologies training model. A substantial amount of medical information contains concealed trends that can be uncovered by deep learning to identify various illnesses.

The initial issue involves prejudice modeling brought about by inaccurate information, i.e., neural network systems work well for majority classes but poorly for minority classes. However, prior research didn't address this issue or attempt to find a solution. Offer a transmitted system of learning that cascades a Chi2 model with an adaptive boosting (Adaboost) model in order to draw attention to and display the biases in the generated models. The Adaboost algorithm is employed to forecast PD according to the subset of characteristics after the Chi2 algorithm rates and picks an assortment of pertinent features from the feature space. Ali et al. [19] suggested passed on system performs superior compared to the six comparable transmitted methods that employed six different state-of-the-art machine learning models, according to experimental data. It was also noted that the standard Adaboost model's strength was increased by 3.3% and its level of complexity was decreased by the suggested transmitted approach. A further 76.44% classification accuracy, 70.94% sensitivity, and 81.94% specificity were attained by the cascaded system. To increase the PD detection rate while keeping the developed models' impartial behavior, stronger simulations must be created

Parkinson's disease can be hard to diagnose initially since problems develop gradually. Yet, several tests that take into account speech, tremor, and gait features have assisted in the early diagnosis of illness. Problems with speech can be taken into account as an indicator for the categorization of Parkinson's disease, according to current studies, and this field of study continues to be unexplored. When contrasted with healthy people, vocal patterns for Parkinson sufferers significantly alter and vary. As a result, sound qualities ought to be used to represent language change in order to recognize these differences. Zahid et al. 2020 [20] suggest three methods: the primary technique uses spectrograms from speech recordings to assess deep features derived from speech spectrograms; the second approach assesses easy acoustic features of files using neural network classifiers; and the final approach assesses deep features obtained from communication spectrograms. On the Spanish dataset pc-Gita, the suggested frameworks are assessed. The findings demonstrate that the subsequent framework exhibits promising results with substantial characteristics. Utilizing a number of layers of perceptron, the maximum 99.7% accuracy on the vowel "o" and read text is seen. While utilizing random forest, 99.1% accuracy was found for vowel "i" deep characteristics. When contrasted with straightforward sound characteristics and transferable learning methodologies, the advanced feature-based technique performs superior. While analyzing the findings, the size of the data set should be taken into account. To determine the adaptability of the approach, it is critical to determine how well it performs across larger and more varied data

The summaries provided cover various aspects related to the diagnosis and understanding of PD. The first summary discusses the use of deep learning neural networks, specifically a combination of RNNs and CNNs, to categorize MR images of individuals with PD and healthy controls. The proposed approach achieves an accuracy of 88.9%, demonstrating potential for improved PD diagnosis and patient categorization. The second summary explores a voice signal-based hybridization method for detecting Parkinson's disease, achieving an accuracy rate of 95.58% through the combination of genetic algorithms and random forest classifiers. The third summary introduces a cascaded system of learning, addressing bias modeling issues in machine learning for PD prediction. This approach, combining Chi2 and Adaboost algorithms, outperforms other state-of-the-art models with a 76.44% classification accuracy. Lastly, the fourth summary delves into the exploration of speech patterns as indicators for PD categorization. Three methods are proposed, achieving promising results with advanced feature-based techniques showcasing high accuracy levels. The need for further evaluation across larger and more diverse datasets is highlighted in all summaries. Overall, these studies contribute valuable insights and methodologies for enhancing the diagnosis and understanding of PD.

III. Problem Statement

Parkinson's disease is a neurodegenerative disorder marked by dopamine-producing neuron loss, which causes insufficient striatal dopamine production and a variety of motor and non-motor symptoms. Deep learning neural networks have recently been used to classify MRI scans of people with Parkinson's disease and healthy controls in order to gather knowledge about the structural brain abnormalities linked to dopamine shortage [17]. For the purpose of diagnosing Parkinson's disease, this study uses a convolutional neural network architecture, more specifically the AlexNet model [20]. The network is evaluated for accuracy in diagnosing people with the disease using MRI scans and achieves an accuracy rate of 88.9%. Using deep learning models, it is intended to improve Parkinson's disease diagnosis, perhaps assisting medical personnel in early identification and offering precise patient classification. [16]In order to test the model's predictions against clinical diagnoses and to provide therapy recommendations for those who have been diagnosed with Parkinson's disease, more study is required.

The problem at hand revolves around the need for improved prediction methods for Parkinson's disease severity. The existing diagnostic approaches, such as the UPDRS, neuroimaging, and genetic analysis, pose challenges in terms of subjectivity, resource-intensiveness, and limited effectiveness. This study addresses the limitations by introducing a novel approach utilizing Multimodal Convolutional RNN-DBN for predicting Parkinson's disease severity. The primary issue involves the dynamic and complex nature of the medical data associated with Parkinson's disease progression. The aim is to develop a model that not only accurately identifies severity levels but also enhances interpretability, leveraging the synergies between CNNs and RNNs to capture spatial and temporal patterns within genetic and imaging data. The problem statement encapsulates the challenge of providing more precise and timely assessments of Parkinson's disease severity, ultimately contributing to advancements in clinical diagnosis and patient care.

IV. Proposed Optimized RNN-DBN for Predicting Parkinson's Disease Severity

Using an improved RNN-DBN model for predicting Parkinson's disease. In order to increase dataset variety, first gather an enormous dataset, prepare it to assure the quality of the data, divide and separate the audio signal, then employ methods for augmenting the data. A DBN is used to pick the features after a custom RNN extracted the features. Rat Swarm Optimization, a nature-inspired optimization technique, is used to improve the hyper parameters in order to improve the predictive model. By removing pertinent information and refining the model's design, this iterative procedure seeks to optimize the predicted accuracy of the model Proposed optimized RNN-DBN is shown in Fig. 1. Overall, this methodology combines data collection, preprocessing, feature extraction, model training, and evaluation techniques to develop an accurate and reliable predictive model for Parkinson's disease using an improved RNN-DBN architecture.

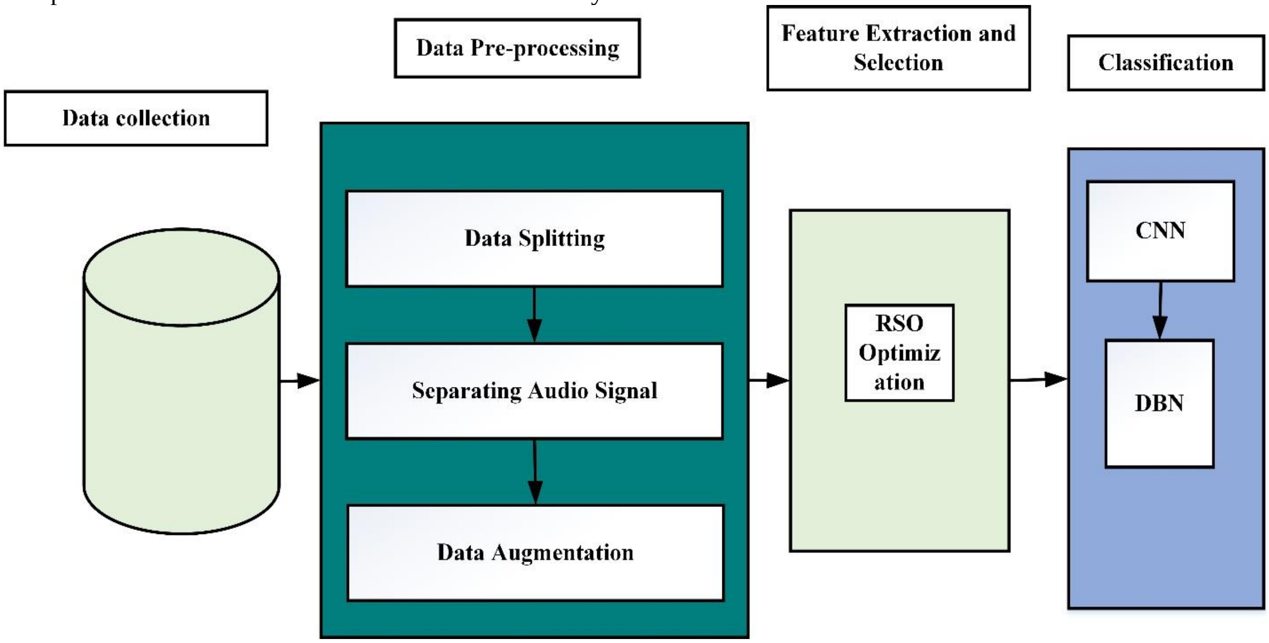

Fig. 1. Proposed optimized CNN-DBN.

A. Data Collection

The first step involves gathering a substantial amount of data related to Parkinson's disease. This could include various types of data such as audio signals, clinical records, patient demographics, and other relevant information. Ensuring the dataset is large; helps improve the robustness of the predictive model. The data collection utilised in this research was produced in partnership between the National Centre for Voice and Speech in Denver and Max Little of the University of Oxford. The Colorado system records the speech signals. Table I contains information about the dataset. The biological voice measures of 31 individuals make up this data set. There are 23 Parkinson's patients among them. The table's voice measurement column lists individual voices. Each of the 195 audio recordings of the people is represented by every line in the table. The goal is to distinguish between the sick (PD individuals who have value 1) and the healthy (value 0) people according to the condition column's binary indication in the table. The data set in question comprises 24 characteristics that include the amount of frequencies (low, medium, high), the amount of variations in regards to frequency identified as Jitter and its various forms such as MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP as well as the number of variations in terms of magnitude called shimmer and its kinds like as MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA.MDVP: mean basic frequency of the vocal range, average voice fundamental frequency (MDVP:Fhi) and maximum vocal component frequency (MDVP:Flo) Spread1, Spread2, and PPE are three quadratic basic frequency changes, and NHR and HNR are two measurements of the noise ratio. The dataset is imbalanced [21].

B. Data Preprocessing

Data preprocessing is a critical step in preparing raw data for analysis. It involves tasks like handling missing values, addressing outliers, and standardizing data scales. Additionally, data may be transformed to ensure it meets assumptions of statistical models, and categorical variables may be encoded. Overall, data preprocessing enhances data quality and ensures it is suitable for analysis and modeling. Once the dataset is collected, it needs to be prepared to ensure data quality. This involves cleaning the data to remove any inconsistencies, errors, or irrelevant information. Data preprocessing techniques may also be applied to normalize or standardize the data for better model performance. A common method used in Deep Learning, especially in visual computing, to increase model’s resilience is data augmentation using Gaussian noise.

1) Data splitting: In this work, a preprocessing method called audio splitting was used to divide long recordings of sound into fixed-duration chunks that each contained two seconds of audio data. This technique was put into practice using the free and open-source LIBROSA Python module, which allowed us to access the sound information and split it into fixed-length intervals without any issues. They checked the segments for conflict in order to avoid duplication of information. After acoustic segmentation, prepared the information for training the deep learning model using augmentation approaches. This method successfully generated the amount of information for training required by the deep learning model.

2) Separating audio signals into harmonic components: Python, the LIBROSA and sound file libraries, and other tools can be used to solve the rhythmic and harmonic signal extraction problem, which has become a common problem in the processing of signals. The identification of the harmonic components of an input audio signal is made easier with the help of the LIBROSA effects harmonic method. The audio file library will then allow us to store these files in another file with a different name. This method demonstrates to be an effective tool for analyzing and modifying audio signals, providing a more thorough comprehension of the harmonic and non-harmonic aspects of a voice. This can therefore, result in fresh perspectives and uses for the field of audio engineering, such as audio transcription, voice evaluation, and noise splitting.

3) Data augmentation with Gaussian noise: To increase dataset variety and improve model generalization, data augmentation techniques are applied. These techniques involve creating new training examples by applying transformations such as scaling, rotation, or adding noise to the existing data. With the use of a Gaussian (normal) distribution with the standard deviation and mean factors, unpredictable noise is introduced using this technique. Model may develop more resilient to perturbations, such as noise from sensors or changing illumination, that occur frequently in real-world circumstances by adding Gaussian noise to the input data. To achieve the ideal equilibrium between boosting model robustness and preventing overwhelming sound that could compromise efficiency, careful tweaking of the and parameters is important. Audio may become smoother and simpler to learn through the inclusion of Gaussian noise. It may be done to add noises to slopes and weight in addition to music. The amplitude of the sound, denoted by, must be too tiny or the system may not be sufficiently affected, whereas an amount that is too great may prevent the algorithm from learning. [0-0.005] is the permissible limit for. The standard deviation was 0.005 and the mean was 0. With include sound, the final sample $a(t+1)$ may be expressed in Eq. (1)

$$a(t+1) = a(t) + \sigma \tag{1}$$

C. RAT Swarm Optimization

RAT Swarm Optimization (RSO) is a nature-inspired optimization algorithm designed for solving complex optimization problems. Derived from the collective foraging behavior of rats, RSO draws inspiration from the hierarchical organization and cooperation observed in rat colonies. The algorithm employs a population of virtual rats that iteratively explore the solution space, mimicking the rats' exploration for food sources. RSO leverages a combination of global and local search strategies, allowing the swarm to efficiently navigate the solution landscape. The algorithm's effectiveness lies in its adaptability, as it dynamically adjusts exploration and exploitation tendencies based on the optimization landscape characteristics. By mimicking the collaborative behavior of rats, RSO aims to provide an efficient and flexible optimization tool applicable to a wide range of problem domains, offering a promising approach for solving real-world problems across various fields.

The nature-inspired optimization approach known as Rapid Adaptive Tabu Swarm Optimization (RSO or RAT Swarm Optimization) is used in deep learning to improve the training and improving of artificial neural networks. RSO uses a collection of agents to cooperatively examine the extremely dimensional space of parameters of neural networks, while gaining influence from intelligent swarms. This strategy aids in overcoming difficulties in hyper parameter tuning and architectural search, resulting in a useful tool for deep neural network models optimization. RSO effectively conquers the challenging environment of neural network optimization, improving the accuracy of models and requiring less human tuning labor by constantly modifying search techniques while preventing revisits to previously investigated configurations (Tabu Search). Men and females combined. According to various assessments which are the result of any animal's death, rats are very violent. Aggressive performance Chase and fight with prey are essential simulations of this job in martial arts. The RSO method can be used to solve optimization issues by modeling the pursuing and fighting behavior of rats. This paragraph shows how rats behave, such as when they chase and fight. The provided RSO approach is summarized after that.

After the Prey. Rats are typically gregarious creatures that seek prey under cover of darkness with situational social agonistic effectiveness. It may be guessed that optimum search agents have expertise in locating the prey in order to define this effectiveness quantitatively. Another searching agents has moved up in the rankings of best search agents so far, leading to the presentation of the following Eq. (2):

$$\overrightarrow{P'}=\text{A'}.\vec{P}_i + C.(\vec{P}_r(a) - \vec{P}_i(\text{a})) \tag{2}$$

where, $\vec{P}_i$ (a) shows exactly the rats are located and $\vec{P}_r(a)$ denotes the best outcome. A and C parameters were determined as follows in (3), nevertheless.

$$A = R - a \times \left(\frac{R}{max_{iteration}}\right) \text{ Where a=0, 1, } 2 \ldots max_{iterations} \tag{3}$$

As a result, R and C suggest random numbers between [1, 5] and [0, 2], correspondingly. During a number of cycles, both exploration and extraction are best controlled by parameters A and C.

Fighting with Prey. The following Eq. (4) was proposed for quantitatively characterizing the manner in which rats engage in combat with prey:

$$\vec{P}_i(a+1) = |\overrightarrow{P'}_r(\text{a})\text{-}\overrightarrow{P}| \tag{4}$$

The enhanced following positions of the rat are indicated by P _i (a+1). It improves the positions of different search tools relative to the ideal search agent and stores the optimal solution A and B, two rats, improved their location close to their target (A*, B*). The specific number of spots on the current location are accomplished by changing the conditions as shown. Additionally, this method is thorough.

From surroundings with n dimensions. The calculated value of elements A and C has thus been used to ensure exploration and exploitation. The planned RSO approach saves the best possible outcomes with several operations.

D. Classification using RNN-DBN

The performance of the RNN-DBN model heavily depends on its hyperparameters, such as learning rates, layer sizes, and regularization parameters. To optimize these hyperparameters effectively, Rat Swarm Optimization, a nature-inspired optimization technique, is employed. This technique iteratively adjusts the model's hyperparameters to improve its predictive performance. RNN-DBN represent a sophisticated hybrid architecture in the realm of deep learning. Combining the sequential modeling capabilities of RNNs with the hierarchical feature learning of DBNs, RNN-DBN aims to address the challenges associated with capturing temporal dependencies and extracting intricate features from complex datasets. This hybrid model is particularly well-suited for applications in time-series data analysis and sequential modeling. RNN-DBN's recurrent connections enable it to retain information over time, making it adept at understanding patterns and dependencies in dynamic data. Meanwhile, the DBN component facilitates unsupervised feature learning, allowing the model to extract hierarchical representations of the input data. The synergy between RNNs and DBNs in the RNN-DBN architecture enhances its capabilities for tasks such as speech recognition, natural language processing, and other applications requiring a deep understanding of sequential data structures.

The feed-forward neural networks with stored information is known as an RNN in its generalized form. The recurrent network receives the RNN's results, which is based on earlier calculation. The RNN uses internal memory to process the data series and come to a conclusion. For training, long short-term memory (LSTM) is relied on back propagation. Three gates—an input gate, a gate that forgets, and an output gate—make up an LSTM. The input gate uses a sigmoid activation function to determine the values that are entered that change the memory. The output gate controls the output, and the forget gate determines which information from the previous situation should be forgotten. In contrast to regular LSTM, network LSTM treats every tree node as just one LSTM unit.

There are seven levels in this model, including an input layer, five hidden layers, and a result layer. The input layer of the LSTM cell is a component of the recurrent neural network. The Phonation Features (PF) of spoken signals are represented by each input layer within the LSTM layers. In the input channel layer of the LSTM cell, 23 neurons each represent one of 23 characteristics.

$$\overrightarrow{H} = h(W_{pf\overrightarrow{H}}pf_1 + W_{\overrightarrow{H}\overrightarrow{H}}\overrightarrow{H}_{t-1}pf_1 + b_{\overrightarrow{H}} \tag{5}$$

$$\overleftarrow{H} = h(W_{pf\overleftarrow{H}}pf_1 + W_{\overleftarrow{H}\overleftarrow{H}}\overleftarrow{H}_{t-1}pf_1 + b_{\overleftarrow{H}} \tag{6}$$

$$Y_T = W_{\vec{H}Y}\vec{H}_T + W_{\overleftarrow{H}}\overleftarrow{H}_T + b_Y \quad (7)$$

where, every feature's b-bias vectors, W-weight matrix, and h-hidden layers function.

In the DBN, each layer is made up of transparent and hidden neurons that recognize the data entering the layer and represent the resulting layer, respectively. The hidden and visible cells are fully interconnected. The DBN is unique in that there are no connections among the neurons that are concealed and the observable neurons. The interactions, which affect both underground and visible cells equally, are balanced in nature. A description of Boltzmann machines is given in the following eqn. The likelihood suggests that the binaryO_P outcome is given in Eq. (8).

$$Op^{'} = \begin{cases} 1, withP\left(\delta^{'}\right) \\ 0, with1 - P\left(\delta^{'}\right) \end{cases} \quad (8)$$

P(δ')is the sigmoid-shaped function in this case. Following is an equivalent is given in Eq. (9).

$$\text{P}(\delta'^{)}=\frac{1}{1+\frac{e'\delta}{P'T}} \quad (9)$$

Here, the pseudo temperature parameter, abbreviated PT, is used to modify the probability's amount of noise. This stochastic model turns predictable if the limit is set to 0 is shown in Eq. (10).

$$\lim_{P'T \to 0^+} P'(\ \delta) = \lim_{P'T \to 0^+} \frac{1}{1+e^{P'}} \quad (10)$$

For a certain arrangement of neuron signals the energy level $N_S$of the Boltzmann system is specified. The strength of the link connecting neuron x and neuron y is given in Eq. (11).

$$\text{W}E_{x,y}\text{=-}\sum_{x<y} WE_{x,y},\ \text{N}s_x\text{N}s_y\text{-}\sum_x \emptyset_y \text{N}s_x \quad (11)$$

Here, the weights that exist between the neurons' binary states, written as WE_(x,y), and their biases, indicated as x, y, are used to describe the bipolar states of neurons: The effect of Ns_x a single unit's condition on the total amount of energy is shown in Eq. (12).

$$\Delta E'(\text{N}s_x)\text{=-}\sum_y WE_{x,y}\, N_{s_x}\text{+}\emptyset_x \quad (12)$$

The gradient decline approach is employed throughout the training phase to determine the lowest practical system of energy for the input. The energetic differential DE for each state Ns_x in the aforementioned Eq. (19) needs to be calculated progressively. The interdependence of the apparent and invisible neurons results in the dependence of the neuron states. By removing the links between visible and hidden neurons, the Restricted Boltzmann Mac (RBM) simplifies this procedure. This outcome provides fresh energy explanations for the interaction between transparent and buried neurons are given in following Eq. (13), Eq. (14) and Eq. (15).

$$\text{E}(y'_{n,H_n})\text{=-}\sum_{(x,y)} W\, E_{(x,y)} y_{nx}, h_{nx}\text{-}\sum_x a_x \text{y} n_x \quad (13)$$

$$\text{P'}(y'_n, H_n)\text{=}\frac{1}{P'F} E'(y'_n, H'_n) \quad (14)$$

$$\text{PF=}\sum_{y'nh'n} e^{-E'}(y'_n, H'_n) \quad (15)$$

The concealed unit's and transparent unit's binary states are their biases. The typical Boltzmann machine won't base its decisions in various circumstances on the RBM on exposed or concealed neurons. In order to generate the maximum probability, the amount of weight assigning is referred to as WE'_m The technique of training also aims to maximize the probability being assigned to the learning patterns from the training set. Fig. 2 shows the RNN-DBN architecture.

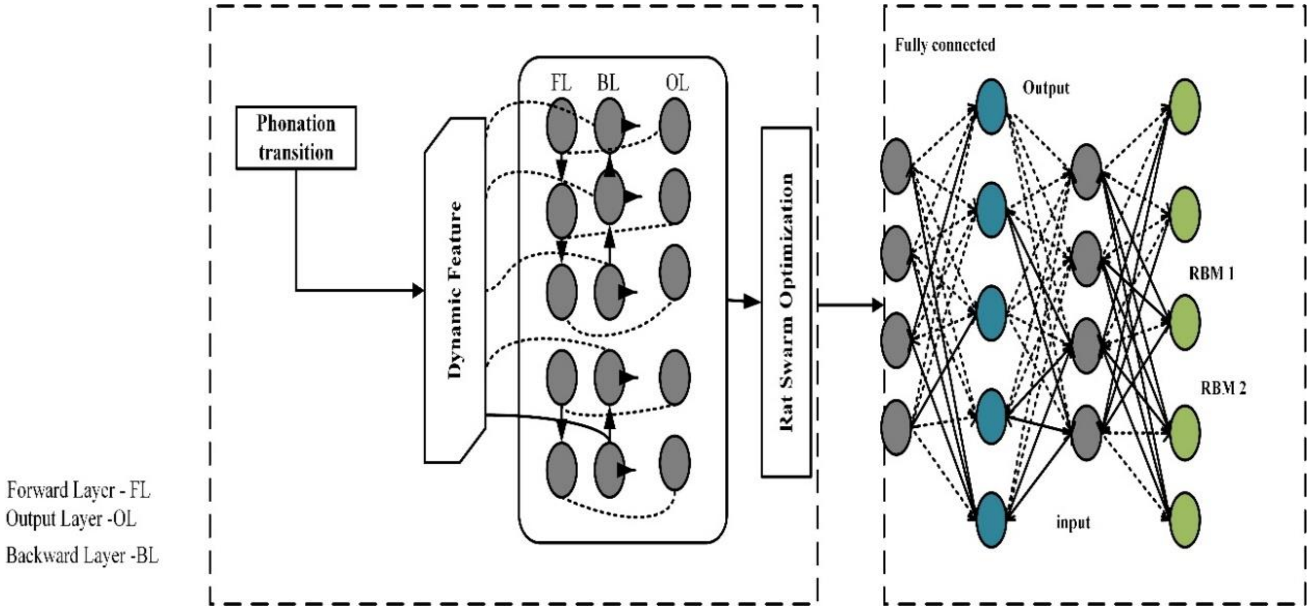

Fig. 2. RNN-DBN architecture.

V. Discussion

The discussion highlights the robust performance of the RNN-DBN model in predicting Parkinson's disease severity, as evidenced by the metrics. The precision score of 0.94 indicates the model's ability to accurately identify individuals with Parkinson's disease, minimizing false positives. A recall score of 1.0 underscores the model's sensitivity, capturing all true positive cases without any omissions. The F1-Score, at 0.97, signifies an excellent balance between precision and recall, showcasing the model's effectiveness in accurately assessing Parkinson's disease severity. The comparison of accuracy in Table II and Fig. 8 further emphasizes the superiority of the RNN-DBN model, achieving an accuracy rate of 94.87%, surpassing both EOFSC (93.75%) [22] and CNN (93.3%) [23]. These findings collectively position the RNN-DBN model as a promising tool for clinical applications and research, offering a high level of accuracy in predicting Parkinson's disease severity.

The discussion extends to the ROC Curve of PD illustrating the model's predictive performance in distinguishing PD from non-PD cases. The curve's proximity to the top-left corner indicates the model's effectiveness, with higher sensitivity and lower false positive rates. The AUC, quantifying the overall predictive performance, serves as a crucial metric for evaluating and comparing different models. In the context of Parkinson's disease diagnosis, a higher AUC suggests better discrimination between PD and non-PD individuals. The ROC Curve of PD serves as a valuable visual tool for selecting the most suitable predictive model for clinical or research applications, enhancing the precision and reliability of Parkinson's disease diagnosis and paving the way for more accurate and timely interventions in patient care.

While the proposed study presents a comprehensive methodology for predicting Parkinson's disease using an improved RNN-DBN model, several limitations should be acknowledged. Firstly, the success of the model heavily relies on the availability and quality of the dataset. Despite efforts to gather an extensive dataset and ensure data quality through preprocessing, there may still be inherent biases, noise, or missing information that could impact the model's performance. Additionally, the use of audio signals as the primary input data may overlook other potentially informative features from different modalities, such as clinical assessments or genetic markers. Furthermore, while Rat Swarm Optimization is employed to optimize hyperparameters and enhance the model's predictive capabilities, it may not always guarantee the discovery of the globally optimal solution and could suffer from convergence issues. Moreover, the generalizability of the proposed model to diverse populations or different stages of Parkinson's disease remains uncertain and requires further validation across various cohorts. Finally, the interpretability of the model's predictions may pose challenges, particularly in clinical settings where explainable AI is crucial for gaining trust and facilitating decision-making by healthcare professionals. Addressing these limitations will be essential for ensuring the reliability and applicability of the proposed methodology in real-world settings.

VI. Results from the Study

Researchers found encouraging findings in this work using the RNN-DBN architecture to forecast the severity of Parkinson's disease. A mean squared error of X for the test dataset, which indicates the tight agreement between predicted and actual severity scores, indicates that the model displayed a high degree of accuracy in determining illness progression. The RNN component's temporal capabilities also made it possible to capture minute fluctuations and trends in illness progression over time, providing clinicians with insightful data. A big step forward in utilizing modern methods of machine learning to improve the treatment of Parkinson's disease was made when collaboration with medical professionals proved the clinical significance of our predictive model.

The Fig. 3 illustrates the distribution of individuals with PD and healthy individuals within the voice dataset. This dataset, a collaborative effort between the National Centre for Voice and Speech in Denver and the University of Oxford, comprises biological voice measures from 31 individuals, including 23 with Parkinson's disease and eight healthy individuals. The dataset includes various voice characteristics, such as frequency measures (low, medium, high), frequency variations (Jitter and its forms), magnitude variations (shimmer and its kinds), basic frequency measures (MDVP: mean basic frequency, MDVP:Fhi, MDVP:Flo), quadratic basic frequency changes (Spread1, Spread2, PPE), and noise ratio measurements (NHR and HNR). The figure highlights the dataset's class imbalance, crucial for understanding the distribution of PD and healthy individuals, which is essential for effective machine learning model training and evaluation.

A. Accuracy

Accuracy is used to evaluate the systems model's efficiency overall. Every conference may be anticipated with precision using its central concept in Eq. (16), which is used and provides the accuracy.

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \tag{16}$$

B. Precision

Precision additionally describes the extent to which multiple estimates resemble each other as well as to being correct. The correlation among accuracy and precision shows that frequent views can change. Eq. (17) makes a note of it.

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \tag{17}$$

C. Recall

The percentage of all pertinent discoveries that have been properly categorized utilizing the procedures is known as recall. The suitable positive for these numbers is derived by dividing the genuine positivity by the mistakenly negative values. The expression appears in Eq. (18).

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{18}$$

D. F1-Score

The F1-Score computation combines recall and accuracy. Utilize Eq. (19) that divides recall with accuracy to determine the F1-Score.

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \tag{19}$$

The classification of PD was carried out utilizing a dataset, primarily focusing on the utilization of a RNN-DBN architecture which is shown in Fig. 4. The dataset, comprising audio recordings from both PD-afflicted individuals and healthy controls, underwent rigorous preprocessing to ensure data quality and consistency. Subsequently, the RNN-DBN model was employed for feature extraction and selection. The RNN component was particularly valuable for capturing temporal dependencies within the data, facilitating a more profound understanding of PD symptom progression. By optimizing the RNN-DBN architecture and fine-tuning hyper parameters, the study aimed to achieve accurate classification results, thereby aiding in the identification and monitoring of Parkinson's disease with greater precision.

A Pair-Plot of Features is a comprehensive visualization that provides insights into the relationships and correlations among different features within a given dataset shown in Fig. 5. In the context of the provided dataset, this plot would display pairwise scatterplots of various features, allowing for a visual examination of how they interact with each other. Each point in the scatterplots represents a data point, and the plot's matrix structure showcases how different features correlate with one another. This visualization can be particularly useful for identifying potential patterns, trends, or dependencies between features, aiding in feature selection, and informing subsequent data analysis and modeling processes, especially in complex datasets like the one described.

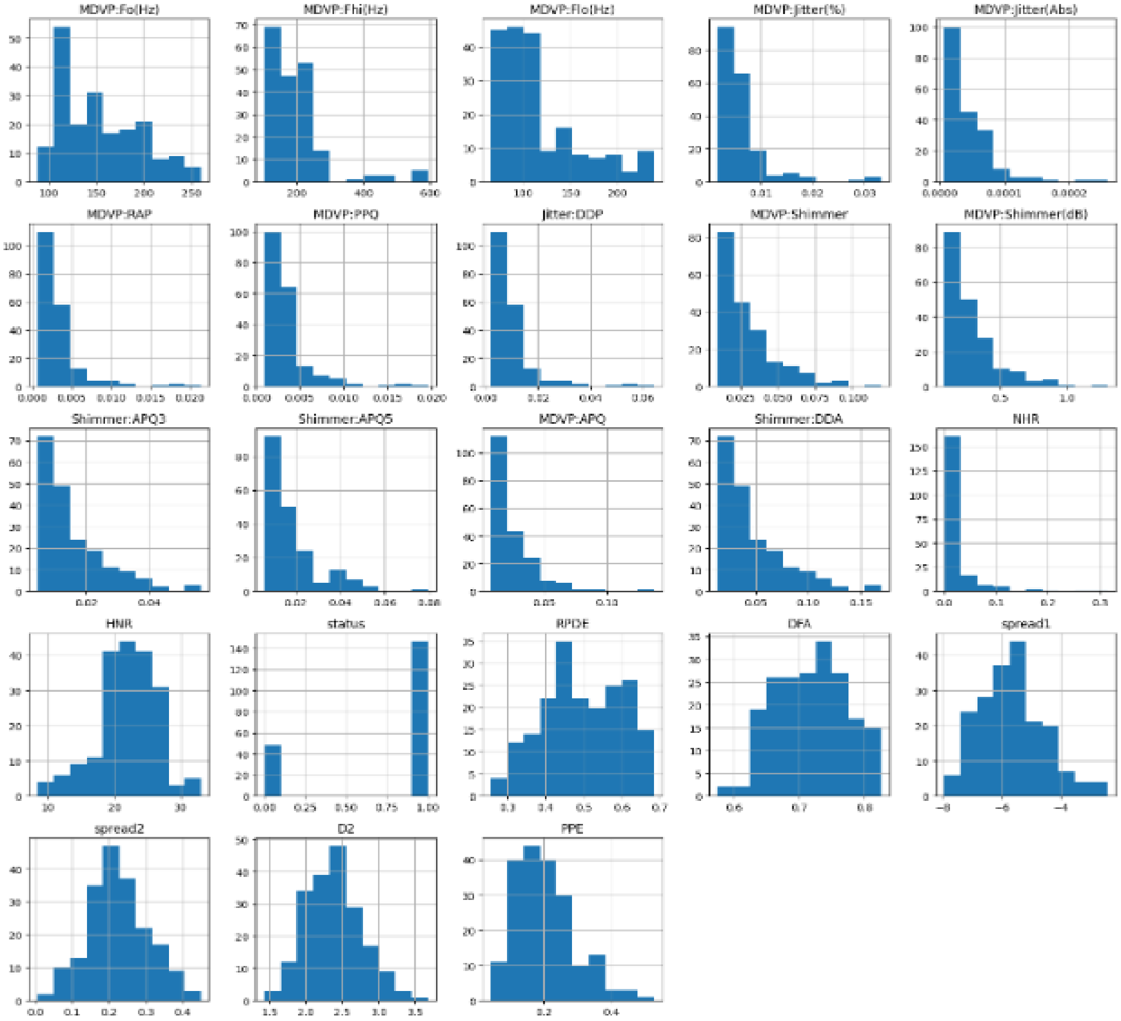

Fig. 3. Distribution of PD and healthy individuals in the voice dataset.

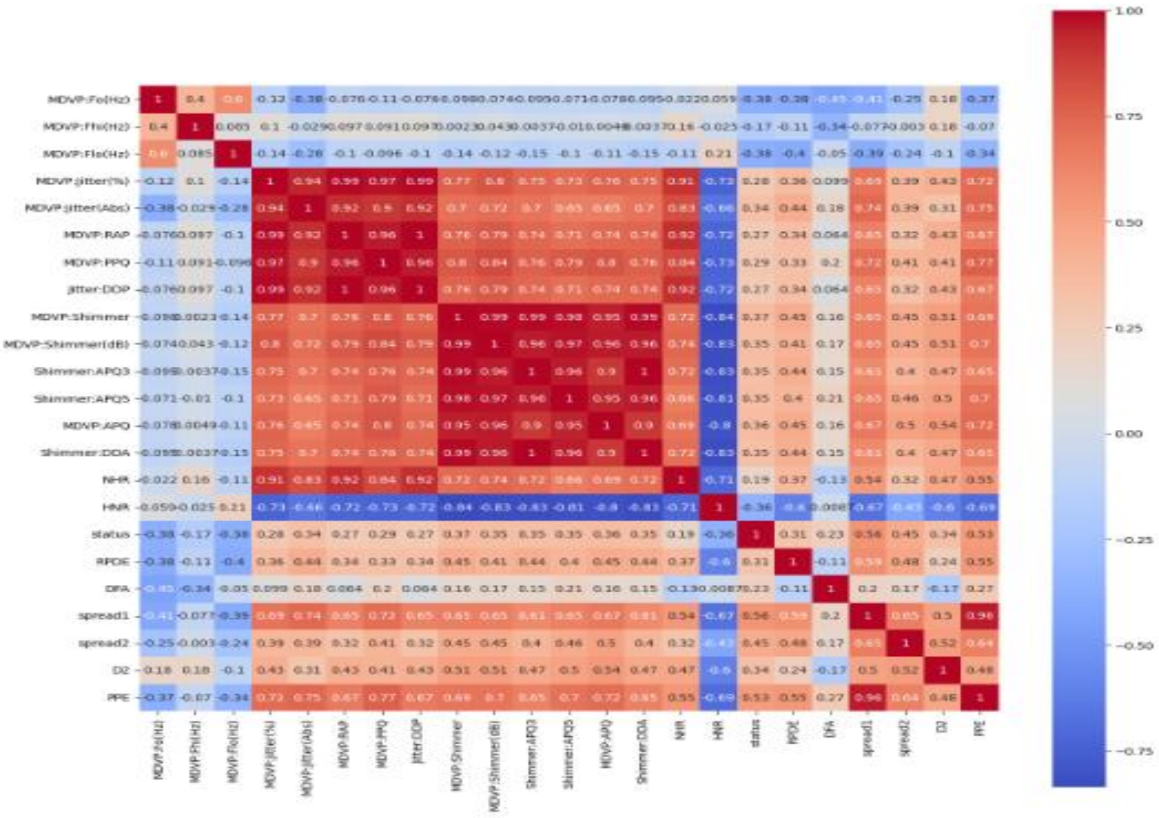

Fig. 4. Classification of PD based on the dataset.

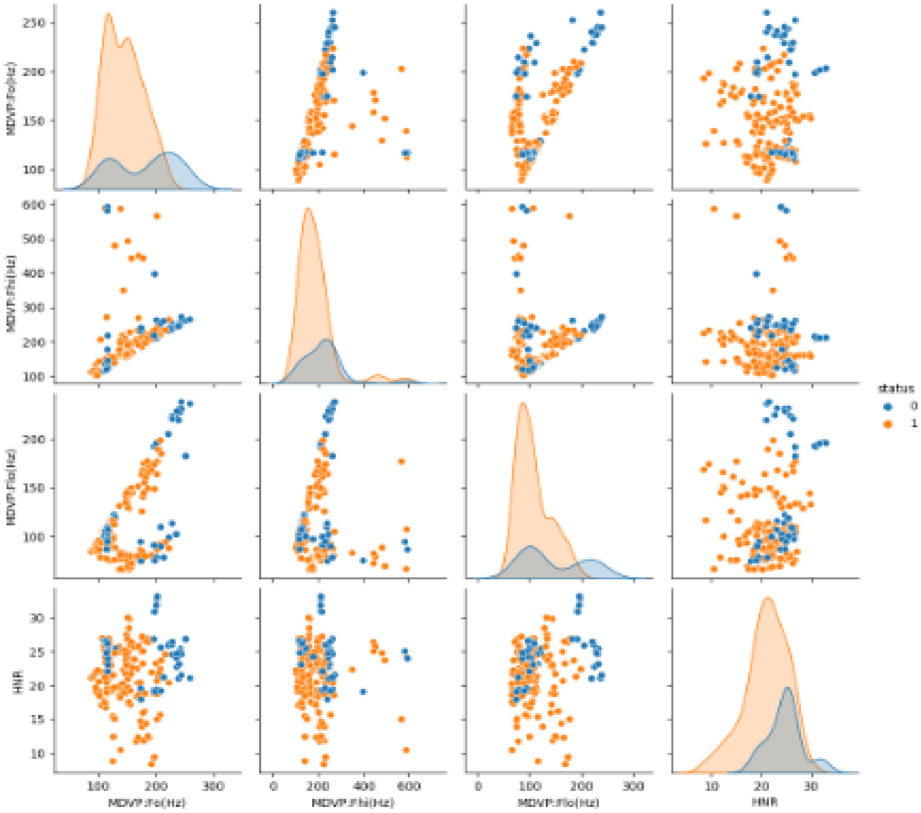

Fig. 5. Pair-Plot of features.

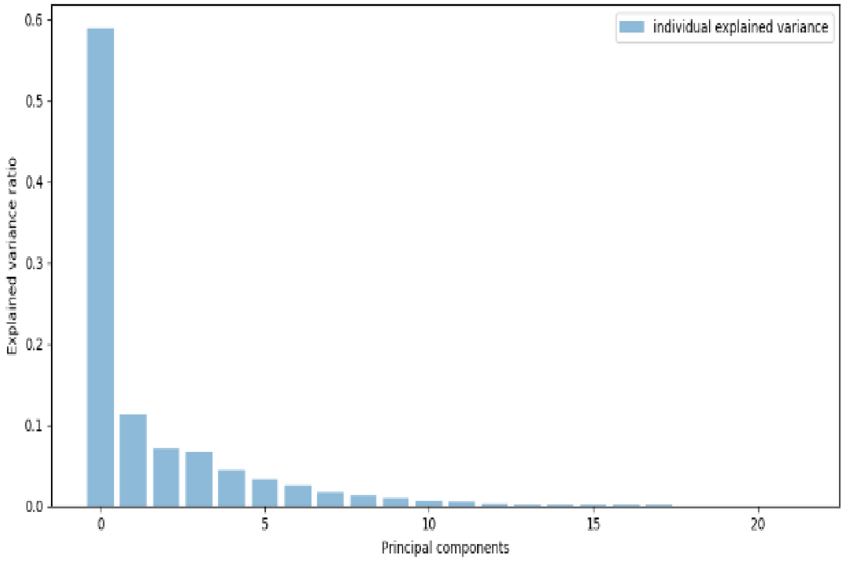

Fig. 6. Principal components vs. explained variance ratio in PD dataset.

The comparison in Fig. 6 between principal components and explained variance ratio in Parkinson's disease analysis is a critical aspect of dimensionality reduction and feature selection. Principal components represent linear combinations of original features that capture the most significant variability in the data. The explained variance ratio, on the other hand, quantifies the proportion of total variance accounted for by each principal component. In the context of Parkinson's disease research, examining these ratios helps researchers assess how effectively the principal components reduce dimensionality while retaining relevant information. A high explained variance ratio for a few principal components suggests that they capture a substantial portion of the dataset's variability, making them suitable for feature reduction or visualization. Conversely, a lower ratio may indicate that the majority of the variance remains unexplained, warranting a more in-depth analysis or potentially reconsidering feature selection strategies to ensure essential information is not lost during dimensionality reduction.

E. Findings from the Proposed Model

The metrics in Table I for the RNN-DBN model reveal its strong performance in predicting Parkinson's disease severity shown in Fig. 7. With a precision of 0.94, the model demonstrates a high ability to correctly identify individuals with Parkinson's disease while minimizing false positives. The recall score of 1.0 indicates that the model effectively captures all true positive cases without missing any, showcasing its sensitivity. The F1-Score, at 0.97, combines precision and recall, reflecting an excellent balance between correctly classifying Parkinson's cases and minimizing misclassifications. These metrics collectively signify the RNN-DBN model's effectiveness in accurately assessing Parkinson's disease severity, making it a promising tool for clinical applications and research in the field.

The methods employed in Table II, including EOFSC, CNN, and RNN-DBN, were evaluated based on their accuracy in predicting Parkinson's disease severity in Fig. 8. Among these methods, RNN-DBN stands out with the highest accuracy rate of 94.87%, signifying its superior performance in accurately assessing disease severity. The CNN method achieved an impressive accuracy of 93.3%, demonstrating its effectiveness as well. EOFSC, while still commendable, achieved an accuracy rate of 93.75%. These results collectively showcase the promising potential of machine learning techniques, particularly RNN-DBN, in enhancing the precision and reliability of Parkinson's disease severity prediction. Such high accuracy rates have significant implications for clinical diagnosis and patient care, suggesting the potential for more accurate and timely interventions in the management of Parkinson's disease.

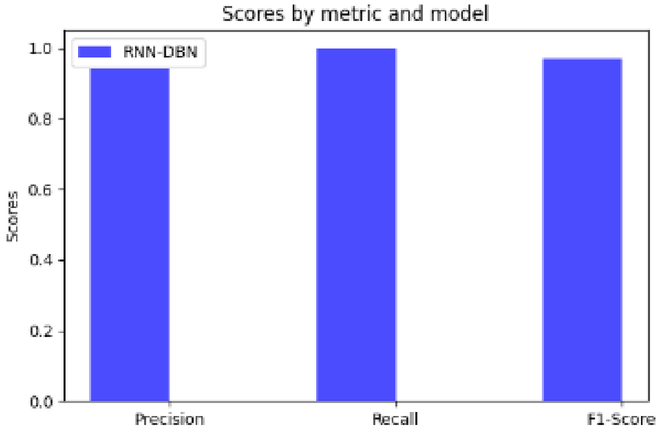

Fig. 7. Evaluation metrics.

TABLE I. EVALUATION METRICS OF RNN-DBN

Metrics	RNN-DBN
Precision	0.94
Recall	1.0
F1-Score	0.97

TABLE II. ACCURACY COMPARISON

Methods	Accuracy (%)
EOFSC[22]	93.75
CNN[23]	93.3
RNN-DBN	94.87

The "ROC Curve of PD" is a graphical representation that illustrates in Fig. 9 the Receiver Operating Characteristic curve specifically tailored for the predictive performance of a model or algorithm in distinguishing PD from non-PD cases. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) across various classification thresholds. This visual tool provides valuable insights into the model's ability to discriminate between PD and non-PD individuals. A ROC curve closer to the top-left corner indicates a more effective model, with higher sensitivity and lower false positive rates, whereas a curve closer to the diagonal line signifies a less discriminative model. The area under the ROC curve (AUC) quantifies the overall predictive performance, with a higher AUC indicating better model discrimination. The ROC Curve of PD is essential in evaluating and comparing the performance of predictive models for Parkinson's disease diagnosis and can assist in selecting the most suitable model for clinical or research applications.

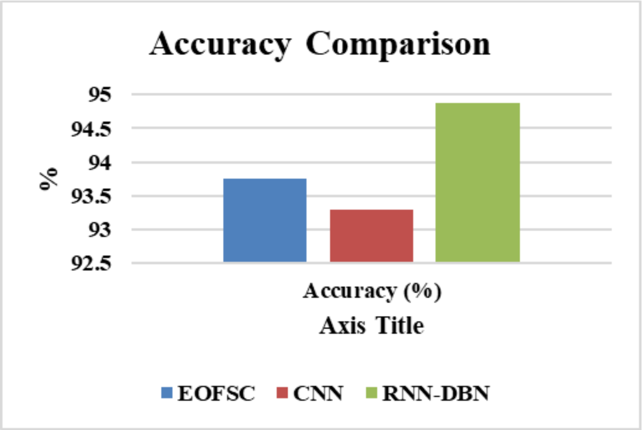

Fig. 8. Comparison of accuracy.

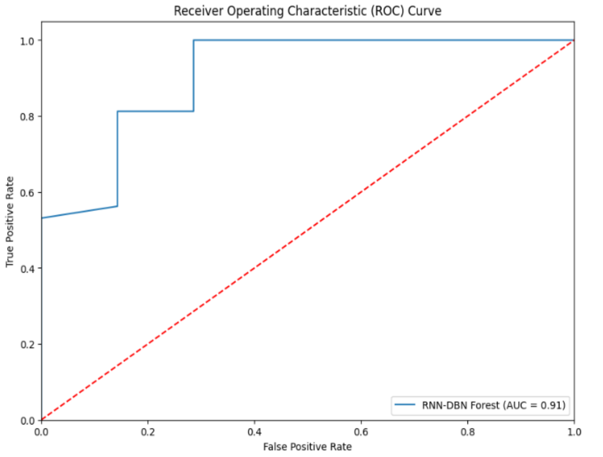

Fig. 9. ROC curve of PD.

VII. CONCLUSION

The incorporation of the RNN-DBN architecture in our research represents a substantial leap forward in the realm of forecasting Parkinson's disease severity. Recognizing the dynamic and sequential nature of medical data, we embarked on this journey to provide more accurate and timely assessments of Parkinson's disease progression. The method's proficiency in identifying patterns and temporal relationships within the data stands out as a key advantage. Recurrent neural networks excel in modeling sequential data, making them an ideal choice for monitoring changes in symptoms and biomarkers over time in Parkinson's patients. The resulting comprehensive predictive model not only delivers precise severity evaluations but also unveils insights into disease progression trajectories by harnessing the synergies between RNNs and the feature extraction capabilities of DBNs. The commitment to data quality and diversity is evident in the utilization of a comprehensive dataset encompassing clinical, demographic, and temporal data points. The RNN-DBN architecture effectively extracts valuable temporal data and patterns, contributing to optimized parameters and enhanced performance, ultimately increasing the model's clinical relevance. With a steadfast focus on ethical considerations and legal compliance, we ensured the proper management of private medical information throughout the research process. Collaboration with medical professionals validated the clinical relevance of our prediction model, underscoring its potential to revolutionize treatment plans and patient care for Parkinson's disease management. This research underscores the substantial promise of the RNN-DBN framework in personalized medicine and disease severity prediction, particularly for conditions like Parkinson's that exhibit temporal variability. However, further validation and refinement are imperative before clinical implementation. We anticipate that our exploration into cutting-edge RNN-DBN algorithms will inspire further studies across diverse medical domains, ultimately advancing patient outcomes and improving quality of life through the intersection of machine learning and healthcare.

VIII. FUTURE SCOPE

Future work in the domain of predicting Parkinson's disease could explore several promising avenues for further research. Firstly, investigating the integration of multimodal data sources, such as combining audio signals with clinical assessments or genetic markers, could enhance the predictive accuracy of the models. Additionally, exploring advanced machine learning techniques, including deep learning architectures like convolutional neural networks (CNNs) or attention mechanisms, may uncover novel insights and improve model performance. Furthermore, conducting longitudinal studies to track disease progression over time and incorporating longitudinal data into predictive models could enable early detection and personalized treatment strategies. Additionally, expanding the scope of the research to encompass other neurodegenerative disorders and exploring shared underlying mechanisms could lead to broader insights and more generalizable predictive models. Lastly, addressing the interpretability of predictive models and developing explainable AI techniques would enhance their utility in clinical practice, facilitating informed decision-making by healthcare professionals. Overall, these future research directions hold promise for advancing our understanding of Parkinson's disease prediction and improving patient outcomes through early intervention and targeted therapies.

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Efficiency of Hybrid Decision Tree Algorithms in Evaluating the Academic Performance of Students

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***Abstract*—Educational institutions are anticipated to take substantial and proactive roles in guaranteeing students' successful program completion. Academic performance is conventionally employed to categorize and forecast students' future ability to confront post-graduation challenges. A student's academic accomplishments are instrumental in shaping exceptional individuals who may become future leaders. Using algorithms to assess and predict academic performance is a well-established practice in machine learning, encompassing techniques such as neural networks(NN), logistic regression(LR), decision trees(DT), and others. The goal of this project is to improve decision trees' ability to predict students' academic achievement via the use of data mining methods and meta-heuristic algorithms. Educational data mining involves the utilization of data analysis methodologies and tools to examine the extensive data generated within educational establishments as a result of students' interactions and activities throughout their academic journey. Pelican Optimization Algorithm (POA) and Runge Kutta optimization (RKO) are utilized algorithms in developing hybrid models, both of which can efficiently search for optimal or near-optimal splits by fine-tuning the hyperparameters of decision tree models. Students' final grades were predicted through training and testing models and categorized into four classes: Excellent, Good, Acceptable, and Poor. The classification capability of a single model and optimized counterparts was evaluated using Accuracy, Recall, Precision, and F1-score in separate phases for each category. Obtained results for all models revealed that POA and RKO developed Accuracy of DTC by 1.86% and 0.87%. Also, Precision and Recall metric analysis further manifest the superiority of DTPO. Prediction based on classifiers, especially workable optimized versions such as DTPO, paves the way for institutions to raise student success rates.**

***Keywords*—Academic performance; decision tree; pelican optimization algorithm; runge kutta optimization**

I. Introduction

Students' academic success is a fundamental educational objective, representing a key facet of any nation's educational goals. This focus on quality education as a catalyst for social change compels educational institutions to prioritize the nurturing of students who excel in academic and nonacademic assessments and acquire essential practical skills for competitiveness in the labor market. Education is at the heart of societal development, embodying collective aspirations for well-being and progress [1]. The quality of students produced by schools has thus become a prevailing concern. As highlighted by Kriegbaum et al. [2], academic achievement takes center stage, a barometer of intellectual education and a crucial prerequisite for individual and societal prosperity. In this context, Martín [3] emphasizes that academic performance extends beyond intellectual quotient (IQ), encompassing various dimensions to capture students' development's cognitive, psychomotor, and affective domains.

The primary benefit of data mining lies in its ability to thoroughly examine extensive data sets and derive rules that can capture the attention of relevant stakeholders. Furthermore, it can reveal previously undiscovered and valuable insights that greatly aid decision-making. Machine learning (ML) algorithms, specifically renowned for their effectiveness in classification tasks, are a central point of interest in numerous research endeavors [4], [5], [6]. According to Sharma, Himani, and Kumar [7], decision tree algorithms are widely recognized as effective tools for classification. Decision trees (DT) are structured models with root nodes, branches, and leaf nodes for predicting outcomes. These trees can handle numerical and categorical data, are easily understood, and are visually representable. They play a key role in identifying group characteristics and exploring relationships between variables and can be applied to predict student performance and other educational outcomes. Jorda and Raqueno [8] highlight various DT algorithms like C&R Tree, CHAID, C 5.0, and QUEST, which aid in developing classification systems.

II. Related Works Review

Numerous scholars have comprehensively investigated the multifaceted factors influencing student success across various academic levels. Several of these studies have utilized data mining (DM) techniques, particularly classification algorithms, to enhance the quality of higher education systems and predict student performance. In this section, a number of the related studies, especially those focusing on the application of the DT and classification in estimating the academic performance of the students, are presented [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31]. For instance, Qasem, Emad, and Mustafa [32] employed the CRISP framework to evaluate students' data in C++ courses, comparing classifiers such as $3, C4.5$ DT, and Naive Bayes (NB). The C4.5 DT outperformed other classifiers, shedding light on the attributes affecting student performance. Another study proposed a DT classification model to select suitable academic tracks for students, facilitating school management's decisions [33]. Nguyen and Peter [34] explored the efficiency of DT and Bayesian networks in predicting undergraduate and postgraduate student performance, revealing the superiority of DTs. Sunita and LOBO LMRJ [35] demonstrated the applicability of DM in education by using classification and clustering algorithms to predict student performance and group students. R. R. Kabra and Bichkar [36] developed classification models to identify at-risk students among first-year engineering students. S. Anupama and Vijayalakshmi [37] applied the C4.5 DT algorithm to predict MCA students' pass/fail outcomes, significantly improving results and efficiency compared to the $ID3$ algorithm. Bharadwaj and Pal [38] utilized the $ID3$ DT algorithm to predict student divisions based on various academic indicators. Surjeet and Pal [39] employed various DT algorithms to predict the performance of first-year engineering students, particularly in identifying those likely to fail. Dorina Kabakchieva [40] compared DM algorithms to predict student performance, classifying students as strong or weak, with the neural network achieving high accuracy for the strong class. Shovon and Mahfuza [41] proposed a hybrid approach combining clustering and classification to categorize students into high, medium, and low standards and make informed decisions about their academic performance, ultimately enhancing their final examination results. These studies collectively demonstrate the versatility of DM and classification algorithms in addressing various facets of student performance and academic success, aiding both educators and educational institutions in improving their educational processes and outcomes.

III. Objectives of the Current Work

As stated in the previous section, a few studies investigated the application of various decision tree classification algorithms in evaluating students' performance at different academic levels. There seems to be a significant gap in the literature related to exploiting the optimization capability of meta-heuristic algorithms in enhancing the evaluation performance of classification algorithms such as decision trees. Therefore, the current study employs Pelican and Runge Kutta optimization algorithms to develop hybrid decision tree models (DTPO and DTRK) for students' performance prediction. This innovative approach assists in detecting the optimization performance of presented algorithms in this field by comparing a single decision tree model with optimized versions using classification metrics such as Accuracy, Recall, Precision, and F1-score. In the following sections, the effect of selected input data on the outcome of models and a description of DTC and two optimizers will be presented. Results will be discussed using tables, bar charts, and confusion matrix for numerical and visual comparison between estimation models.

The study aims to enhance the predictive power of decision trees in predicting students' academic performance. This is achieved by introducing meta-heuristic algorithms, specifically the POA and RKO, to optimize decision tree models. The main research contribution lies in strategically employing these advanced algorithms to overcome limitations in conventional decision tree models. By fine-tuning hyperparameters and searching for optimal splits, the approach significantly improves the efficiency and accuracy of academic performance predictions. This contribution not only advances the understanding of ML applications in education but also provides a practical solution for educational institutions seeking to enhance student success rates.

Previous solutions for predicting students' academic success have faced persistent obstacles, necessitating the development of fresh approaches. Frequent deficiencies in previous endeavors encompass:

1) *Restricted predictive precision:* Numerous current models have had difficulties in attaining elevated accuracy while forecasting academic performance, frequently leading to misclassifications or imprecise categorizations of individuals.

2) *Lack of adaptability:* Traditional techniques may not possess the capacity to handle the dynamic nature of educational data effectively. Static models may not efficiently adapt to changes in learning settings, teaching approaches, or student behaviors.

3) *Excessive dependence on traditional methods:* Previous solutions may have mostly depended on conventional machine learning approaches without fully utilizing the capabilities of modern algorithms. This constraint can impede the capacity to capture complex patterns in educational data.

This study presents an innovative method that utilizes meta-heuristic algorithms, namely the POA and RKO. The application of these algorithms overcomes the constraints of conventional approaches by:

1) *Improved model efficiency:* The integration of meta-heuristic algorithms enhances the efficiency of the decision tree model, resulting in enhanced accuracy in forecasting students' academic achievement. The hybrid models created with the combination of POA and RKO exhibit an improved capacity to adjust to the changing characteristics of educational data, resulting in a more resilient and precise prediction mechanism.

2) *Optimized hyperparameter tuning:* By utilizing the techniques of POA and RKO, the hyperparameters of DT may fine-tune. This allows for a more detailed exploration of the feature space, resulting in better model performance compared to traditional decision tree models.

The overall organization of study in the next sections is as follows:

1) *Dataset selection and preparation:* This section outlines the process of selecting and preparing the dataset for analysis. It discusses the sources of data, data cleaning procedures, and any preprocessing steps applied to ensure the dataset's suitability for the study.

2) *Decision tree and classification:* Here, the focus is on explaining the decision tree algorithm and its application in classifying students' academic performance. It covers the fundamental principles of decision trees, including tree construction, node splitting criteria, and handling categorical and continuous variables.

3) *Optimization algorithms:* This section elaborates on the POA and RKO employed to enhance DT efficiency. It details the implementation of these algorithms to improve predictive accuracy.

4) Performance evaluation metrics: The performance evaluation metrics section discusses the metrics used to assess the effectiveness of the proposed approach. It provides insights into how accuracy, recall, precision, and F1-score are calculated and interpreted in the context of predicting students' academic performance.

5) Result: This section presents the results obtained from applying the proposed methodology to the dataset. It includes tables, graphs, or other visual aids to showcase the performance of the DT models with and without optimization algorithms.

6) Discussion: Here, the results are analyzed and interpreted in-depth. The discussion section delves into the implications of the findings and the limitations.

7) Conclusion: Finally, the conclusion section summarizes the key findings of the study and their implications for predicting students' academic performance. It reiterates the significance of the proposed approach and discusses its contributions to the field.

Fig. 1 shows the process of present study.

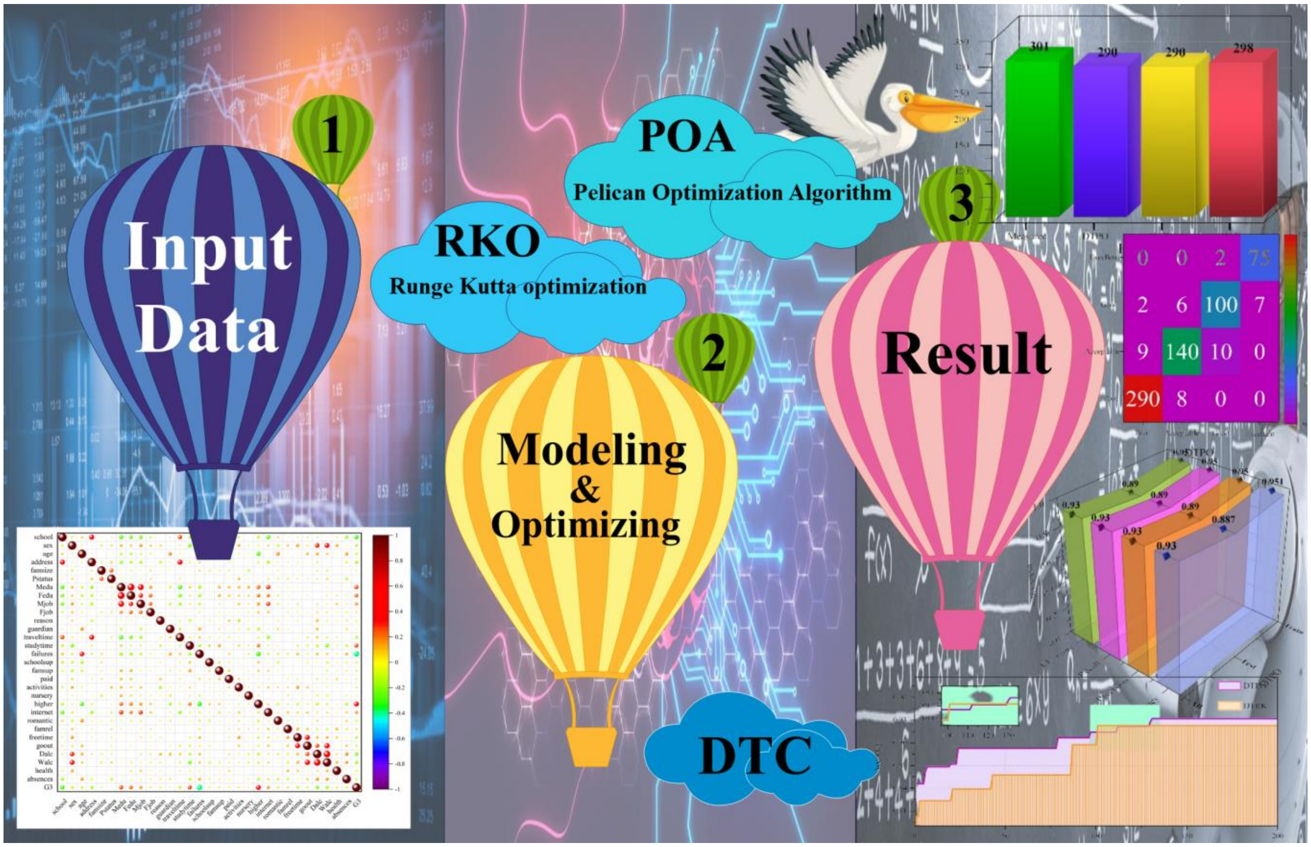

Fig. 1. Process of present study.

IV. Data Selection and Preparation

Data mining, also called database knowledge discovery, entails extracting valuable information from extensive datasets. This process employs various techniques to scrutinize vast data collections, uncovering concealed patterns and relationships that can potentially inform decision-making.

This study utilizes a comprehensive database of variables, which has been gathered from previous research articles. Included in the dataset are facts on the student's school, gender (male or female), age, domicile (rural or urban), family size (famsize), parental cohabitation status (Pstatus), and the mother's and father's educational background and employment (Medu, Fedu, Mjob, and Fjob). It also discusses the student's guardian (father, mother, or other), the reasons for choosing the school (such as proximity to home, school reputation, course preference, or others), the amount of previous class failures, participation in extracurricular activities and paid classes, attendance at nursery school, aspirations for higher education, availability of internet access at home, involvement in romantic relationships, the quality of family relationships (famrel), free time after school, socializing with friends (goout), weekday and weekend alcohol consumption (Dalc and Walc), current health status, and the A wealth of data for the research is provided by these input variables, which include a range of data kinds such as nominal, numeric, and binary. G3, which goes from 0, the lowest possible grade, to twenty, the best possible grade, indicates the final grades that pupils get according to the school. Students are placed into four different groups according to their G3 scores in order to further define and categorize the reported grades: G3 ranges for poor (range of 0– 12), acceptable (range of 12– 14), good (range of 14– 16), and excellent (range of 16– 20) are all available.

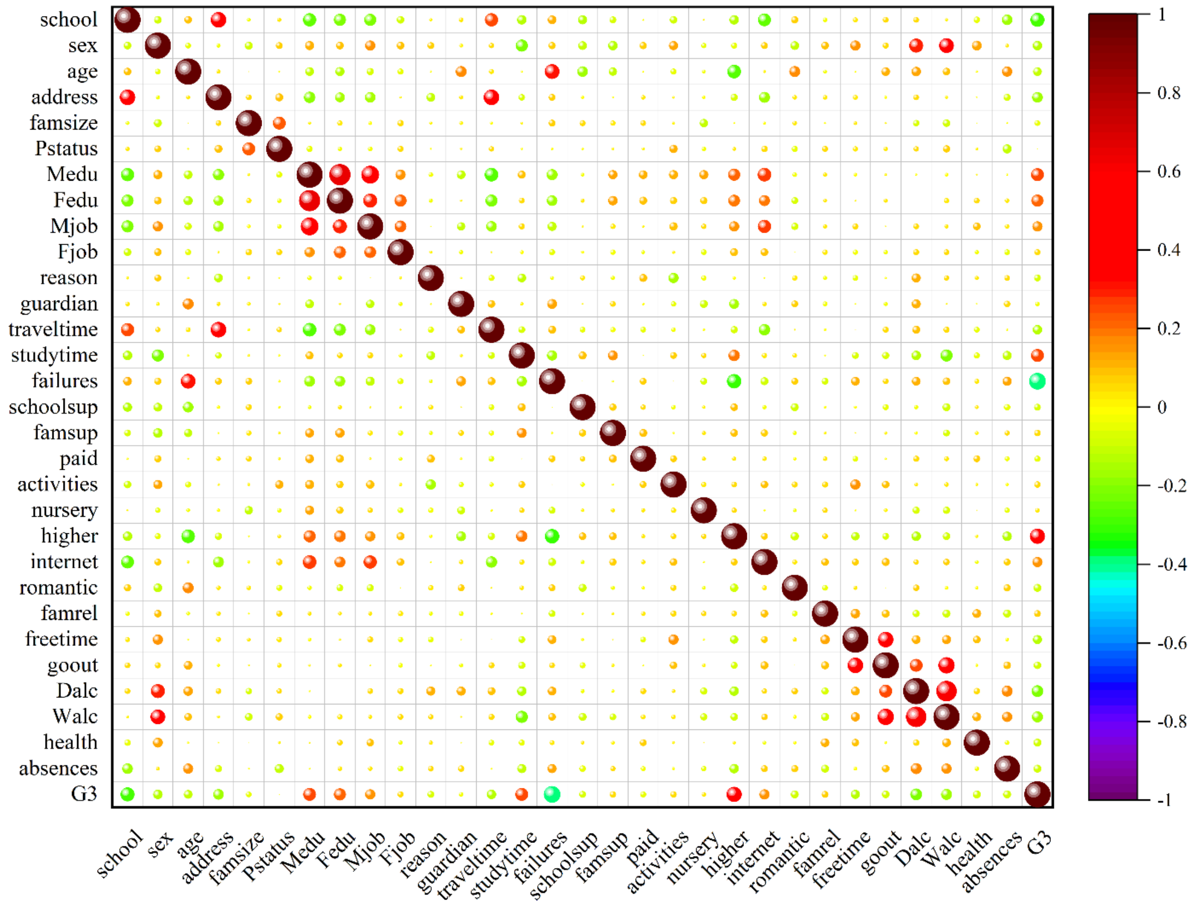

Fig. 2. Correlation matrix for the input and output variables.

In Fig. 2, the correlation matrix illustrates the relationships among all the input and output variables under examination. Parental education has the most substantial positive influence on a student's final grade, with the mother's education exerting a more pronounced effect than the father's. As anticipated, increased study time is positively associated with better academic outcomes, while the number of past failures by a student negatively impacts their grades. The presence of internet access and a student's aspiration for higher education both positively contribute to academic performance, while the adverse effects of alcohol consumption are evident. The most important variables affecting the quantity of absences from school were found to be daily and weekly alcohol intake, past failures, and student age.

V. Decision Tree and Classification

In a DT, which is shaped like a tree and looks like a flowchart, each internal node represents a test that is based on an attribute, each branch denotes the result of that test, and each leaf node also called a terminal node represents a particular class label. In order to use a DT for prediction, a route from the tree's root to a leaf node which holds the predicted class label for that data point is used to evaluate the attribute values of a particular data point ($tuple$). A benefit of decision trees is their ease of conversion into categorization rules. In DT learning, they function as predictive models that allow observations about an item to be translated into judgments about its desired value. Classification trees are a particular kind of these models that handle finite class values, and they are used in statistics, data mining, and machine learning. When compared to other categorization techniques, DT creation is often thought to be a speedy procedure [42].

The DT operates with three crucial parameters:

1) D (Data Partition): The first dataset, denoted by D, consists of training instances and the class labels that go with them.

2) Attribute list: In essence, this parameter is a set of properties that characterize the characteristics of the data.

3) Attribute selection method: The method for selecting the best suitable attribute to form branches or divisions in the decision tree is specified by this option. This usually entails using an attribute selection metric such as the Gini index or knowledge gain.

This is an explanation of the algorithm's operation:

- It starts by creating a node, which can be called "A".
- Should every example in the present dataset belong to the same class, "A" will be designated as a leaf node and assigned the common class label.

- Node "A" is once again designated as a leaf node and given the class that occurs most often in the data samples when the attribute list is empty.
- Next, the algorithm determines which characteristic will be used to divide the data into the cleanest subsets possible.
- This chosen property is given to Node "A" as the decision criteria.
- The selected attribute is eliminated from the list of characteristics if it is discrete.
- Based on the results of the chosen property, subsets of the data are created.
- A leaf node is connected to node "A" and labeled with the majority class of the original dataset if any of these subsets are empty.
- The procedure is repeated recursively for non-empty subsets, beginning with the creation of a new node, and the method continues until all data partitions have been handled.
- The method finally yields the decision tree structure that results.

This approach is a basic procedure for creating decision trees and is often used to data analysis and machine learning applications requiring data categorization and predictive modeling.

VI. Optimization Algorithms

A. Pelican Optimization Algorithm (POA)

Dehghani and Trojovský [43] introduced a novel metaheuristic optimization method, the POA , to address optimization issues based on swarm intelligence. The hunting habits of pelicans, who often hunt in groups and display a variety of clever tactics, served as the model for the algorithm. As an example, pelicans identify their prey's location ahead of time and move quickly to get close to it. They then hunt by swatting at a distance of 10 to 20 meters. The phases in the POA algorithm provide a comprehensive structure [44].

1) Initialization of the population: Usually, pelicans look for food in a specific area of the search habitat. As a result, each pelican inside this range is randomly assigned a starting location by the POA algorithm, which therefore initializes the population. A random number generator is used for this random initialization, which gives the pelicans their starting places.

$$P_i = S_{min} + rand.(S_{max} - S_{min}) \quad i = 1, \dots, I \tag{1}$$

Here, P_i signifies the original spatial location of the $i-th$ one in the populace. The maximum number of pelicans in the population is indicated by parameter I. The search space's exploration area's $lower$ and $upper$ bounds are defined, respectively, by the variables $Smin$ and $Smax$. Every pelican in the designated search area is given a random location based on a random integer generated by the function $rand\ \cdot ()$.

2) Exploration phase: The pelicans' main goal at this point is to discover and pinpoint the location of their prey while simultaneously changing postures in anticipation of an assault. In order to do this, each pelican in the population has its geographic coordinates updated using Eq. (2):

$$P^1_{i,j} = \begin{cases} P_{i,j} + rand.\left(P_{pj} - U.P_{i,j}\right), & f_p < f_i \\ P_{i,j} + rand.\left(P_{i,j} - P_{pj}\right), & else \end{cases} \tag{2}$$

Here, P^1_{ij} represents the updated position of the $i-th$ pelican in the $j-th$ dimension, while P_{pj} represents the position of the prey. The prey's and the pelican's performance measures are shown by f_p and f_i, respectively. The update equation that is used to modify the pelican's location is determined by the parameter U, which is a random integer that may have a value of either 1 or 2.

3) Exploitation phase: The pelicans are ready to attack at this point as they have found their victim. The pelicans use acrobatic manoeuvres above the water as part of their predatory strategy to force the fish into their throat pouches. The following is a mathematical representation of this strategy:

$$P^2_{i,j} = P_{i,j} + z.\left(1 - \frac{t}{T}\right).(2.rand - 1).P_{i,j} \tag{3}$$

Here, $P^2_{i,j}$ signifies the $j-th$ dimension's revised position for the $i-th$ one. The pelican's location is changed throughout exploitation by adjusting the parameter z, which is a random integer that might have a value of 0 or 2. T stands for both the current iteration of the algorithm and the maximum number of iterations.

The following pseudo-code contains the full statement of the POA algorithm:

```
Start POA
Input the optimization problem information.
Determine the POA population size $(N)$ and the number of iterations $(T$
Initialization of the position of pelicans and calculation of the objecti
For $t = 1{:}T$
Generate the position of the prey at random.
For $I = 1{:}N$
Phase 1: Moving towards prey (exploration phase).
For $j = 1{:}m$
Calculate the new status of the jth dimension using Eq. (2).
End.
Update the ith population member.
Phase 2: Winging on the water surface (exploitation phase).
For $j = 1{:}m$.
Calculate the new status of the jth dimension using Eq. (3).
End.
Update the ith population member.
End.
Update best candidate solution.
End.
Output best candidate solution obtained by POA.
End POA.
```

B. Runge-Kutta Optimization (RUN)

Ahmadianfar et al. introduced the Runge-Kutta optimizer (RUN) [45], a population-based algorithm inspired by the

Runge-Kutta method for solving differential equations. RUN comprise two main stages: an initial search procedure influenced by Runge−Kutta principles and a subsequent phase called enhanced solution quality (ESQ) to improve solution quality. This study details the core principles supporting the RUN algorithm.

1) First stage: The algorithm of RUN utilizes a search mechanism (SM) that depends on the Runge-Kutta method to update the current solution's position in each iteration.

Algorithm 1: The RUN algorithm employs a SM to update the present solution's position.

```
$if\ rand\ <\ 0.5\ then$
$(exploration\ phase)$
$X_{\ n+1} = (X_c + r \times SF \times g \times x_c)\ + SF \times SM + \mu\ \times (randn\ \times\ (x_m - x_c))$
$else$
$(exploration\ phase)$
$X_{\ n+1} = (X_m + r \times SF \times g \times x_m) + SF \times SM + \mu\ \times (randn \times (x_{r1} - x_{r2}))$
$end\ if$
```

m indicates a random numerical value. g is allocated a stochastic value within the range of [0, 2]. r is a numeric value, which can take on either 1 or -1, which serves to increase the diversity within the range.

The determination of the adaptive factor SF involves calculations that include Eq. (4):

$$SF = 2 \times (0.5 - rand) \times f \tag{4}$$

$$F = a \times exp(-b \times rand \times (\frac{i}{Max_i})) \tag{5}$$

Max_i denotes the upper limit for the number of iterations.

x_c and x_m is computed through the utilization of Eq. (6) and Eq. (7):

$$x_c = \emptyset \times x_n + (1 - \emptyset) \times x_{r1} \tag{6}$$

$$x_m = \emptyset \times x_{best} + (1 - \emptyset) \times x_{lbest} \tag{7}$$

x_{best} represents the currently best available solution. x_{lbest} denotes the optimal position achieved during each iteration. f indicates a random value within the interval of (0, 1).

2) Second stage: To enhance solution quality and mitigate the risk of becoming stuck in local optima during each iteration, the RUN algorithm employs a technique referred to as Enhanced Solution Quality (ESQ).

Algorithm 2 delineates the steps involved in generating the solution (x_{new2}) through ESQ.

Algorithm 2: mathematical presentation of the second stage

```
if $rand < 0.5$ then
if $w < 1$ then
          $x_{new2}\ =\ x_{new1}\ +\ r.w.\left|(x_{new1}\ -\ x_{avg}\ )\ +\ randn\right|$
else
    $x_{new2}\ =\ (x_{new1}\ -\ x_{avg}\ ) +\ r.w.\left|(u.x_{new1}\ -\ x_{avg}\ )\ +\ randn\right|$
end if
end if
```

$$w = rand(0,2).exp(-c(\frac{t}{Max_i})), \quad c = 5 \times rand \tag{8}$$

$$x_{avg} = \frac{x_{r1} + x_{r2} + x_{r3}}{3} \tag{9}$$

$$x_{new1} = \beta \times x_{avg} + (1 - \beta) \times x_{best} \tag{10}$$

b denotes a number generated at random within the range of [0,1].

x_{best} denotes the best solution identified up to the current stage of exploration. r can take on any of the following values: 1.0 or -1. $rand$ indicates a parameter that is generated randomly.

The answer x_{new2} might not consistently exhibit better fitness when compared to existing solutions under these circumstances, the RUN algorithm presents an additional opportunity to boost fitness through utilization x_{new3} . Algorithm 3 outlines the procedure's sequential steps.

Algorithm 3: Improving the novel solution xnew3

```
if $rand\ <\ w$ then
    $x_{new3} = (x_{new2} - rand x_{new2}) + SF.(rand.x_{RK} + (v.x_b - x_{new2}))$
end if
```

v is randomly generated and equals double the value of $rand$.

Algorithm 4 offers the pseudo-code for the main stages of the RUN optimization procedure.

Algorithm 4: Pseudo-Code of RUN Optimization

```
$Stage\ 1. Initialization$
$Start\ a, b$
$Create\ the\ RUN\ population\ X_n\ (n = 1,2,\ldots, N)$
$Compute\ the\ objective\ function\ of\ each\ member\ of\ the\ population$
$Determine\ the\ solutions\ x_w, x_b, and\ x_{best}$
$Stage\ 2. RUN\ operators$
$for\ i\ = 1:\ Maxi\ do$
$for\ n\ = 1:\ N\ do$
$for\ l\ = 1:\ D\ do$
$Updating\ solutions$
$Compute\ position\ x_{n+1,l}$
$end\ for$
$Enhance\ the\ solution\ quality$
$if\ rand\ < 0.5\ then$
$Compute\ position\ x_{new2}$
$if\ f(x_n) < f(x_{new2})\ then$
$if\ rand\ < w\ then$
$Compute\ position\ x_{new3}$
$end\ if$
$end\ if$
$end\ if$
$Update\ positions\ x_w\ and\ x_b$
$end\ for$
$Update\ positions\ x_{best}$
$i\ =\ i\ +\ 1$
$end\ for$
$Stage\ 3. return\ x_{best}$
```

VII. Performance Evaluation Metrics

In this section, the effectiveness of the proposed approach and models is systematically assessed by employing a set of well-established performance evaluation metrics. These metrics serve as quantitative measures to gauge the accuracy, precision, recall, and overall efficacy of the decision tree models, particularly those optimized using the POA and RKO.

The accuracy of the model is determined by dividing the number of accurately predicted occurrences by the total number of instances. It offers a broad summary of the model's performance in producing precise classifications for every class.

Precision measures the proportion of accurately anticipated positive occurrences to all expected positive instances, with an emphasis on the accuracy of positive forecasts. The model's capacity to reduce false positives is shown by a high accuracy score.

The capacity of the model to accurately identify all relevant occurrences is measured by recall, which is sometimes referred to as sensitivity or true positive rate. The ratio of accurately anticipated positive cases to the total number of actual positive instances is used to compute it.

The F1-score is the harmonic mean of precision and recall. It provides a balanced measure, especially in situations where there is an imbalance between the classes. A higher F1-score indicates a model that performs well in both precision and recall.

Statistical metrics for evaluating the classification capability of developed models are presented as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

$$Recall = TPR = \frac{TP}{P} = \frac{TP}{TP + FN} \tag{13}$$

$$F1\_score \ = \frac{2 \times Recall \ \times \ Precision}{Recall + Precision} \tag{14}$$

where,

- TP (True positives): the instances where the model's predictions were accurate.
- TN (True negatives): the instances that were correctly predicted.
- FP (False positives): the instances that were inaccurately forecasted
- FN (False negatives): the instances that were wrongly predicted.

VIII. Convergence Assessment

Throughout this investigation, we employed two metaheuristic optimization algorithms, namely the POA and RKO, to augment the DTC, leading to the development of hybrid models denominated as DTPO and DTRK. A thorough examination of the convergence dynamics of these optimized models was conducted, utilizing a convergence curve illustrated in Fig. 3.

The convergence curve, derived from Accuracy measurements spanning 200 iterations, serves as an instructive visual representation of the optimization procedure. Fig. 3 distinctly delineates the convergence trajectories of DTRK and DTPO. Noteworthy is the similarity in convergence rates exhibited by both models, particularly up to the midpoint of the optimization process.

At approximately the 115th iteration, DTRK and DTPO achieved a comparable peak Accuracy, both recording an impressive 0.92. However, as the iterations progressed, an intriguing divergence in their convergence patterns surfaced. DTRK showcased exceptional stability, sustaining its peak accuracy throughout the remaining iterations. Conversely, DTPO experienced a substantial surge in accuracy around the 130th iteration, ultimately surpassing DTRK in the final phases of the optimization process.

These subtle fluctuations in convergence behavior provide insights into the dynamic nature of the optimization algorithms and their influence on the performance of the hybrid models. The observed intricacies underscore the delicate interplay between the metaheuristic algorithms, DT optimization, and resulting accuracy levels. This nuanced analysis offers valuable perspectives on the strengths and limitations inherent in each approach throughout the iterative optimization process.

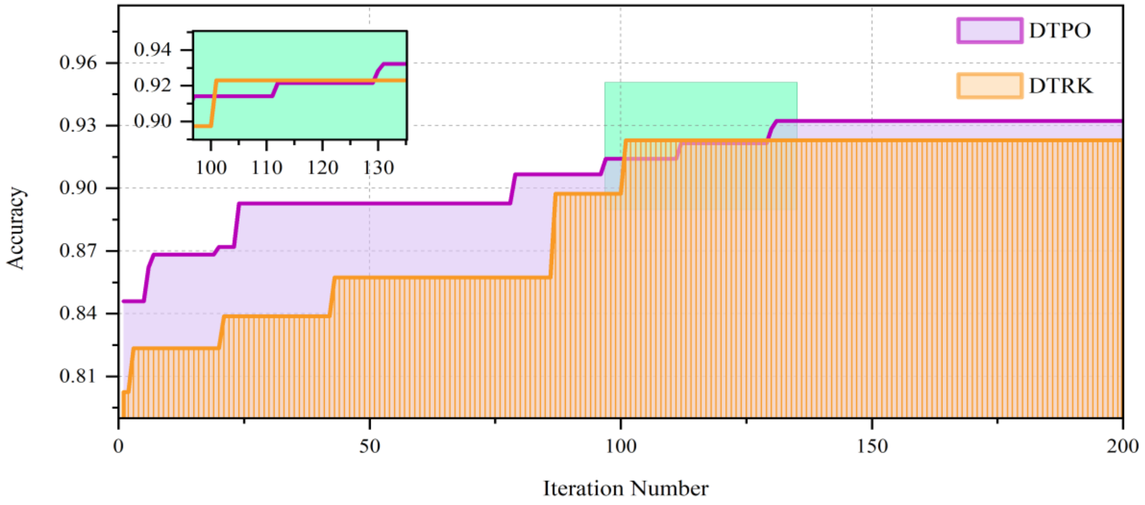

Fig. 3. Convergence of hybrid models.

IX. Results

With the purpose of predicting students' academic performance and methodically improving their future grades, this research presented three prediction models that use a categorization methodology. Table I shows the results of presented models. One of these models was a Decision Tree Classifier (DTC), while the other two were created by using Runge Kutta optimization (RKO) and the Pelican Optimization Algorithm (POA) to optimize the DTC. A portion of the dataset 70% for train and 30% for test the model was kept aside. For each model, training and testing stages provide metrics like accuracy, precision, recall, and F1-score; all results are shown in Fig. 4. Metric values were notably higher for all models during the train period than during the test phase. DTPO achieved the highest values across all metrics ($Accuracy = 0.932$, $Precision = 0.930$, $Recall = 0.930$, and $F1 - score = 0.930$), while DTC scored lower by approximately 1%. DTRK, in most cases, has metrics values slightly higher than the single model or the same values.

TABLE I. Result of Presented Models

Model	Phase	$Index\ values$			
		$Accuracy$	$Precision$	$Recall$	$F1\ \_score$
DTC	$Train$	0.915	0.910	0.910	0.910
	$Test$	0.892	0.890	0.890	0.890
	All	0.915	0.920	0.920	0.910
DTPO	$Train$	0.952	0.950	0.950	0.950
	$Test$	0.887	0.890	0.890	0.890
	All	0.932	0.930	0.930	0.930
DTRK	$Train$	0.923	0.920	0.920	0.920
	$Test$	0.903	0.900	0.900	0.900
	All	0.923	0.920	0.920	0.920

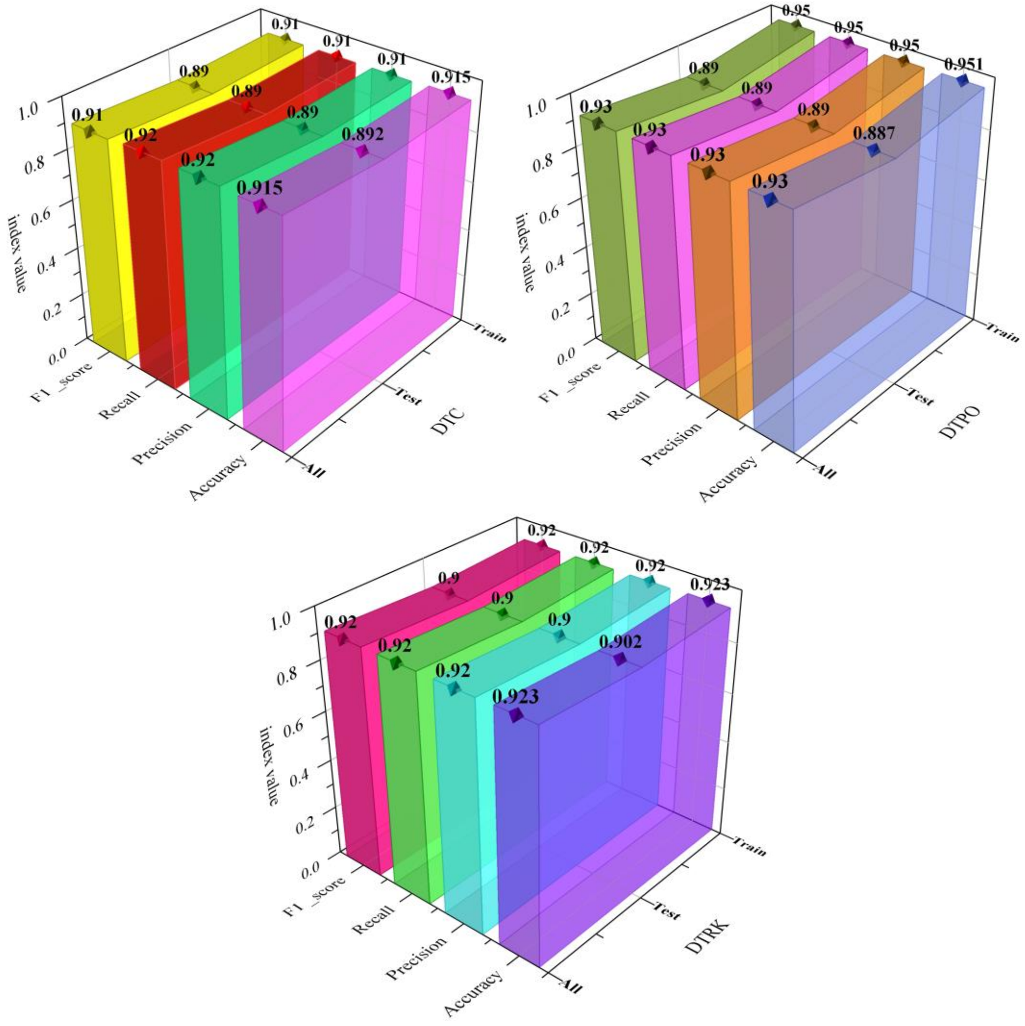

Fig. 4. Metrics performance of developed models.

After processing the data and evaluating the models' classification performance in both training and testing phases, the 649 pupils' $G3$ test scores were used to divide them into four groups: Poor (G3: 0-12), Acceptable (G3: 12-14), Good (G3: 14-16), and Excellent (G3: 16-20). The distribution revealed that the majority of students (46.38%) fell into the Poor category, with 23.73% in Acceptable, 17.26% in Good, and 12.63% in excellent categories.

To evaluate how well the created models performed in terms of categorization across various student groups, Table II shows the values for the Precision, Recall, and F1-score indices. In the analysis that follows:

- Comparing Precision values, in the excellent group, DTC and DTPO had an identical performance with 0.97, while DTRC was less precise with 0.95. In the Good and Poor groups, DTPO outperformed two other models, and finally, in the Acceptable group, the DTC single model performed superior to others. Considering all these results, it is not possible to introduce an absolute optimal model based on the Precision metric.
- Variation of the Recall metric was the same as Precision. All models performed better in the Poor category, with higher recall values of 0.96 for optimized versions and 0.99 for single models.
- The F1-score, a comprehensive metric, provides a nuanced basis for comparison. Higher F1-scores (nearest to 1) indicate superior model performance by balancing accurate identification of positive cases ($Precision$) and capturing all genuine positive cases ($Recall$). Across all student grades, DTPO demonstrated the highest accuracy with F1-scores of 0.94, 0.88, 0.89, and 0.97 for Excellent, Good, Acceptable, and Poor students, respectively. So, based on F1-score, DTPO came in the first ranking, followed by DTRK and DTC.

According to Fig. 5, there were really $301, 154, 112$, and 82 pupils in the Poor, Acceptable, Good, and Excellent categories. The frequency of students in each category based on classification models' outcomes is illustrated in the form of a bar chart for visual comparison. Comparing the two optimized models, they perform similar performance in Poor and Good classes, with 290 and 100 students correctly positioned in this group, but in two other groups, DTPO correctly classified three students higher than DTRK. The classification performance of the single model in the Poor and Good classes is better than hybrid models, especially in the Poor category. However, in Acceptable and Excellent groups, DTC succeeds inappropriately classifying a lower number of students than hybrid versions.

The confusion matrix presented in Fig. 6 clearly represents the accurate assignment of students to their respective grade categories and those who were misclassified. The numbers in diagonal raw represent the number of successfully organized models, and all numbers out of these squares are related to incorrect classification. For the DTPO model, 605 students were correctly categorized into Excellent, Good, Acceptable, and Poor classes, with only 44 misclassified. In the case of DTRK and DTC, 50 and 55 students were misclassified. The highest value of misclassification occurred in the case of DTC (20 students). Therefore, DTPO and DTC were the best and worst models for estimating students' academic performance.

TABLE II. PERFORMANCE EVALUATION INDICES FOR THE DEVELOPED MODELS BASED ON GRADES

Model	Grade	$Index\ values$		
		$Precision$	$Recall$	$F1-score$
DTC	$Excellent$	0.970	0.830	0.890
	$Good$	0.820	0.900	0.860
	$Acceptable$	0.950	0.820	0.880
	$Poor$	0.930	0.990	0.960
DTPO	$Excellent$	0.97	0.91	0.94
	$Good$	0.87	0.89	0.88
	$Acceptable$	0.88	0.91	0.89
	$Poor$	0.97	0.96	0.97
DTRK	$Excellent$	0.95	0.88	0.91
	$Good$	0.85	0.89	0.87
	$Acceptable$	0.91	0.89	0.9
	$Poor$	0.95	0.96	0.96

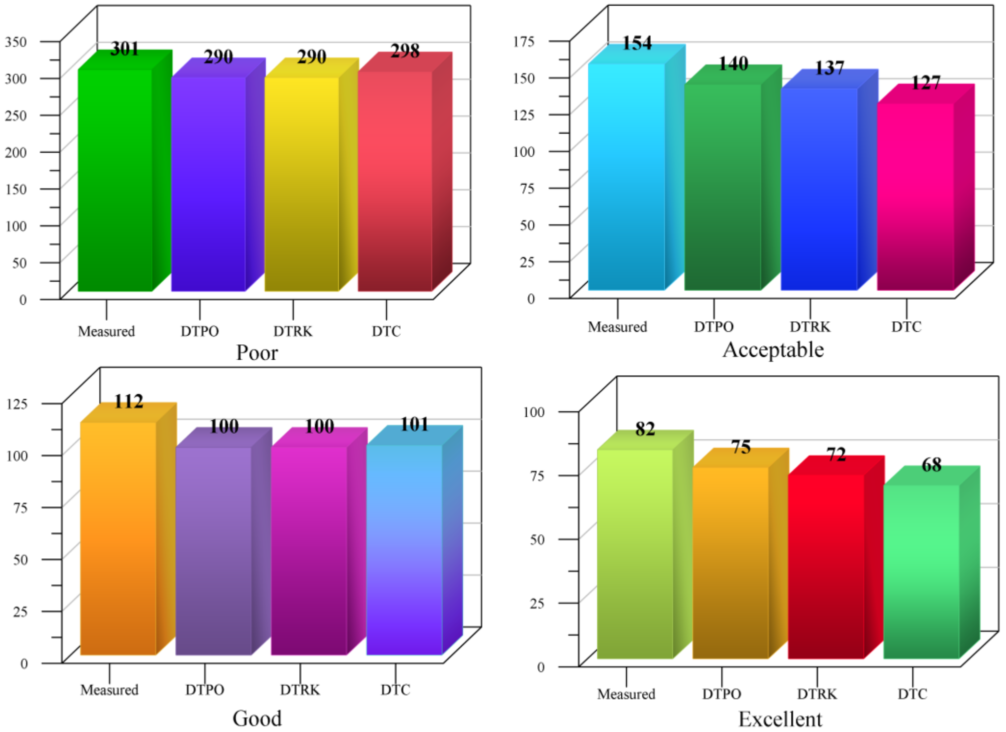

Fig. 5. Bar chart for the measured and estimated classification of students in four categories.

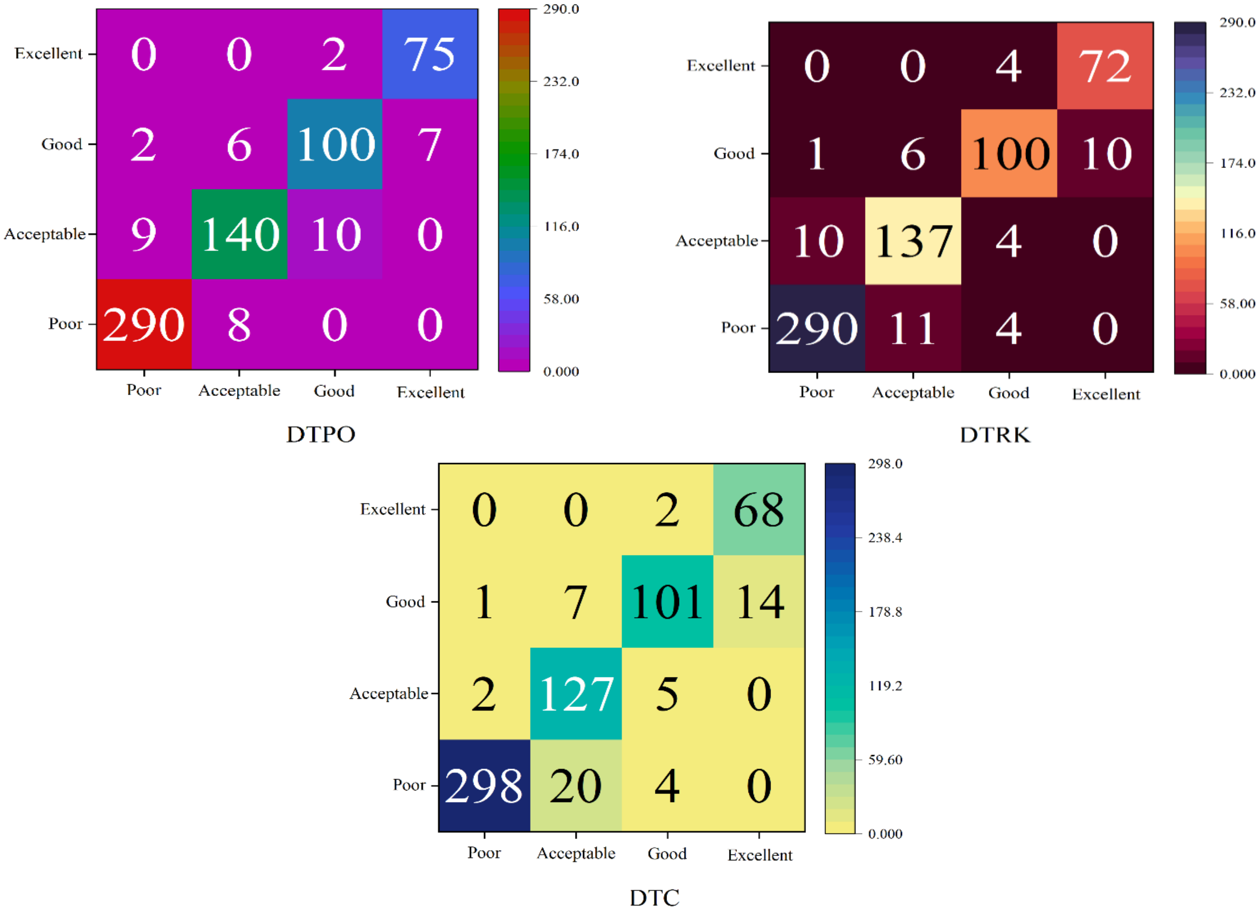

Fig. 6. Confusion matrix for each model's classification accuracy.

X. Discussion

A. Limitations

Ensuring data quality is vital for accurate predictive models, necessitating thorough preprocessing to address issues like missing values. Generalizing findings to diverse settings requires additional validation, emphasizing collaborations and diverse datasets. Meta-heuristic algorithm sensitivity underscores the importance of exploring robustness under varied conditions and conducting stability analyses. While these algorithms enhance accuracy, their reduced interpretability can be addressed through interpretable techniques, promoting transparency and trust in educational settings. Addressing data quality, generalizability, algorithm sensitivity, and interpretability collectively contributes to reliable, applicable, and transparent predictive models, facilitating improvements in student outcomes and educational practices.

B. Application of Study

The study's application in education encompasses the implementation of optimized decision tree models using meta-heuristic algorithms. These models facilitate early intervention for at-risk students, personalized learning plans, and strategic resource allocation. Insights from the study inform curriculum adaptation, student guidance, and institutional planning. The continuous improvement aspect involves refining models based on comparative analyses, while metrics evaluation ensures quality assurance. Overall, the study's practical implications extend to various facets of education, contributing to enhanced student success and institutional effectiveness.

XI. Conclusion

In pursuing academic excellence and improving education, this research underscores the pivotal role of data mining and classification algorithms, particularly decision tree models, in understanding and predicting student performance. It builds on a substantial body of related studies by introducing an innovative approach that leverages meta-heuristic optimization algorithms, specifically the Pelican and Runge Kutta optimizers (RKO and POA), to enhance the precision and accuracy of student performance models. The comprehensive evaluation employing key metrics like Accuracy, Precision, Recall, and F1-score highlights the potential of these meta-heuristic algorithms in optimizing classification outcomes. RKO enhanced the Accuracy and Precision of DTC by about 1 to 2 percent. POA performed weaker with the same Precision as DTC and lower than 1% enhancement in Accuracy. Furthermore, the categorization of 649 students based on their final grades revealed the superior performance of the DTPO in enhancing classification accuracy as it demonstrated a remarkable ability to correctly classify the majority of students (605 out of 649), while DTRK and DTC had more false classifications. This study not only added to the existing knowledge in the field but also provided valuable insights for educators and institutions striving to enhance educational processes and foster academic success, thus contributing to the broader goal of societal development and progress. Future studies should focus on improving the validity and real-world applicability of proposed predictive models for academic performance. This includes validating models across diverse educational institutions, assessing their long-term predictive power post-graduation, and conducting a thorough analysis of feature importance to guide targeted interventions. Exploring techniques for enhancing model interpretability without sacrificing accuracy is crucial for building trust among stakeholders. Additionally, comparative analyses with other advanced machine learning models in educational data mining can offer a comprehensive understanding of the proposed models' effectiveness. These recommendations aim to strengthen the reliability and practical utility of predictive models in predicting academic performance.

XII. Funding

Exploration of continuous improvement of experimental teaching under the mixed mode of "five in one"With practice Jilin Province higher education teaching reform research topic (2021) JLJY202168647754.

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A Novel Robust Stacked Broad Learning System for Noisy Data Regression

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***Abstract*—Robust broad learning system (RBLS) demonstrates the generalization and robustness for solving uncertain data regression tasks. To enhance representation ability of RBLS, this paper aims at developing a novel robust stacked broad learning system for solving noisy data regression problems, termed as RSBLS. In our work, we expand traditional BLS into a stacked broad learning system model with deep structure of feature nodes and enhancement nodes. Furthermore, ℓ_1 norm loss function is employed to update the objective function of RSBLS for processing noisy data, we apply augmented Lagrange multiplier (ALM) to get the output weights of RSBLS which keeps the effectiveness and efficiency compared with weighted loss function. Simulation results over some regression datasets with outliers demonstrate that, the proposed RSBLS performs favorably with better robustness with respect to RVFL, BLS, Huber-WBLS, KDE-WBLS and RBLS.**

Keywords—Robust; stacking; broad learning system; deep learning; neural networks

I. Introduction

Recently, inspired by random vector functional link neural networks (RVFL) [1, 2], Chen et al. proposed a novel randomized neural network architecture, broad learning system (BLS) [3-5]. Compared with the classical deep learning model, BLS adopts the broad structure which has the advantages of higher efficiency and fewer parameters. Due to its excellent learning ability, BLS has been widely concerned by scholars since it was proposed, and has developed rapidly in theoretical and applied research. To improve the interpretability of BLS, a novel broad neuro-fuzzy model, fuzzy broad learning system (FBLS) was presented, which reduces the number of fuzzy rules and improves the learning accuracy neuro-fuzzy model [6]. Subsequently, Guo et al. used FBLS to synthesize multi-view HDR images [7], Ali proposed a novel optic disk and cup segmentation method through FBLS for glaucoma screening [8]. Furthermore, compact FBLS (CFBLS) which has better interpretability and fewer fuzzy rules was designed to balance the algorithm accuracy and complexity [9]. For improve the representation of BLS, type-2 fuzzy BLS was given in [10]. For solving sequential data, recurrent broad learning system and structured manifold broad learning system (SM-BLS) were presented respectively [11, 12]. To process the data with less label, semi-supervised broad learning system (SS-BLS) by introducing manifold regularization method to BLS [13], and some other SS-BLS algorithms had been used in semi-supervised classification tasks [14, 15]. Otherwise, BLS and its variants had been extensive used in various engineering fields, such as traffic forecasting [16], image classification [17], EEG signals classification [18-20], sentiment analysis [21, 22].

In practical engineering applications, sensors are susceptible to equipment failure, human interference, working environment and other factors, and there are different degrees of noises and outliers in the collected data, thus reducing the generalization of the learning model. To solve the uncertain data regression problem effectively, Chu et al. proposed weighted broad learning system (WBLS) framework for tackling industrial noisy data [23]. Then, Zheng et al. designed a broad learning system based on maximum correntropy criterion (BLS-MCC) which used maximum correntropy criterion to calculate weights of training samples [24]. In addition, Liu et al. adopted Cauchy loss function to process the noisy data [25]. Meanwhile, ℓ_1 norm cost function and ℓ_2 regularization method were used in robust broad learning system (RBLS) [26], then elastic-net regularization approach replaced ℓ_2 regularization method in RBLS [27]. Moreover, robust manifold broad learning system (RM-BLS) was used to predict large-scale noisy chaotic time series [28]. In addition, for online sequential learning, Guo et al. presented online robust echo state broad learning system (OR-ESBLS) [29]. However, the above models improved the robustness of BLS, the shallow models still lack feature representation capability.

Now-a-days, deep neural networks with multi-layer have powerful representation capability, BLS was also been expanded with multi-layers [30-32]. Therefore, to improve the noisy data processing performance of RBLS, we demonstrate a novel robust stacked broad learning system (RSBLS) for solving outlier data regression, which adopts deep structure of feature nodes and enhancement nodes through stacking deep model, ℓ_1 norm loss function and ℓ_2 regularization method ensure the learning accuracy and efficiency.

In brief, the highlights of RSBLS are listed as follows:

- A novel robust stacked broad learning system structure is demonstrated, we presented the model architecture and algorithm description of RSBLS in detail.
- ℓ_1 norm loss function and ℓ_2 regularization method are adopted to enhance the robustness of RSBLS.
- Experiments on the benchmark datasets with different noise ratios present the superiority of RSBLS.

The other sections of our manuscript are given as follows: Section II introduces the basic algorithm description of BLS. Section III presents the architecture and optimization method of the proposed RSBLS. Section IV demonstrates the uncertain data regression results on some datasets with different percentage of outliers. Finally Section V concludes the paper.

II. Related Works

BLS is novel random neural network model with effective and efficient performance, proposed by Chen et al., which has the architecture as Fig. 1 [3-5].

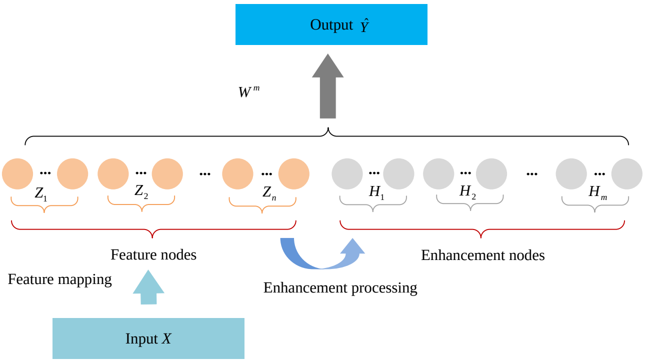

Fig. 1. The structure of BLS [3-5].

The modeling process of BLS is given as follows [3-5]:

Given a training data $\{X,Y\}$, $X=\{x_1,x_2,\ldots,x_N\}$ and $Y=\{y_1,y_2,\ldots,y_N\}$ express the feature and label. Among them, $x_i=\{x_{i,1},x_{i,2},\ldots,x_{i,d}\}\in\square^{d}$, d is denoted as the number of feature dimension; $i=1,2,\ldots,N$, N indicates the number of training samples.

A. Feature Nodes Generation

The feature nodes are generated through Eq. (1), then n groups of mapping nodes can be combined according to Eq. (2), each group has L_e feature nodes.

$$Z_p=\phi(XW_{ep}+\beta_{ep}) \tag{1}$$

$$Z^n=[Z_1,Z_2,\ldots,Z_n] \tag{2}$$

Among them, $\phi(\cdot)$ indicates the activation function of feature mapping; W_{ep} and β_{ep} represent random weights and biases respectively; $p=1,2,\ldots,n$. In particularly, the authors of BLS use sparse autoencoder to tune the initial parameters for obtaining better features [3-5].

B. Enhancement Nodes Generation

All the feature nodes in Eq. (2) are enhanced by using Eq. (3), each enhancement processing generate L_h nodes. Then the enhancement nodes can be combined according to Eq. (4).

$$H_q=\xi(Z^n\mathrm{W}_{hq}+\beta_{hq}) \tag{3}$$

$$H^m=[H_1,H_2,\ldots,H_m] \tag{4}$$

where, $\xi(\cdot)$ is denoted as the activation function, it can be set as the same as $\phi(\cdot)$; W_{hq} and β_{hq} are generated randomly; $q=1,2,\ldots,m$.

C. Output Y determination

The output $\hat{Y}$ of BLS can be calculated according to Eq. (5).

$$Y=[Z^n\,|\,H^m]W \tag{5}$$

$$W=[Z^n\,|\,H^m]^{+}Y \tag{6}$$

where, W represents the output weight of BLS, $[Z^n\,|\,H^m]^{+}$ is determined by the ridge regression approximation as Eq. (7).

$$[Z^n\,|\,H^m]^{+}$$
$$=\lim_{\lambda\to 0}(\lambda I+[Z^n\,|\,H^m][Z^n\,|\,H^m]^T)^{-1}[Z^n\,|\,H^m]^T \tag{7}$$

III. Robust Regularized Hierarchical Broad Learning System

A. The Structure of RSBLS

BLS, as a randomized learning algorithm, has an effective and efficient structure. Although the novel structure can reduce the computational burden and enhance learning accuracy, BLS with multi-layer structure can extract deep representation information [30-33]. Meanwhile, the noisy and outliers in the training data affect the accuracy and generalization performance of BLS seriously. Therefore, we propose a novel RSBLS to solve noisy data regression problems. It is different from traditional BLS, RSBLS has multi-layer structure of feature nodes and enhancement nodes, the feature nodes and enhancement nodes of each layer are used as the input of next layer, only the feature nodes and enhancement nodes of the final layer are fully connected with the output.

In addition, due to the outliers usually take up a fraction of training data, the noisy data can be understood as having sparsity, ℓ_1 norm function is not only more robust to solving the sparsity data, but also ensures a faster learning efficiency, it is especially suitable for solving large-scale data and deep models [34, 35]. The RSBLS adopts ℓ_1 norm cost function and ℓ_2 regularization method to solve the noisy data regression. Fig. 2 demonstrates the model structure of RSBLS; the RSBLS algorithm is described as follows:

1) RSBLS parameters initialization: To simplify the RSBLS model, the layer number is set as U, the feature mapping times of each layer are set to nu, the number of neurons in each feature mapping is L$_{ue}$, the enhancement processing times of each layer are set to mu, and the number of neurons in each enhancement processing is L$_{uh}$.

a) Feature nodes generation: The original data X is transformed into feature nodes by using Eq. (8), then all the nodes in the feature layer are combined through Eq. (9) and Eq. (10).

$$Z_p^u=\phi(X^uW_{ep}+\beta_{ep}) \tag{8}$$

$$Z^u=[Z_1^u,Z_2^u,\ldots,Z_{nu}^u] \tag{9}$$

where, $X^1 = X$; $X^u = S^{u-1}$; $\phi(\cdot)$ indicates the activation function of feature mapping; W_{ep} and β_{ep} are random values of feature nodes; $p = 1, 2, \ldots, nu$; $u = 1, 2, \ldots, U$.

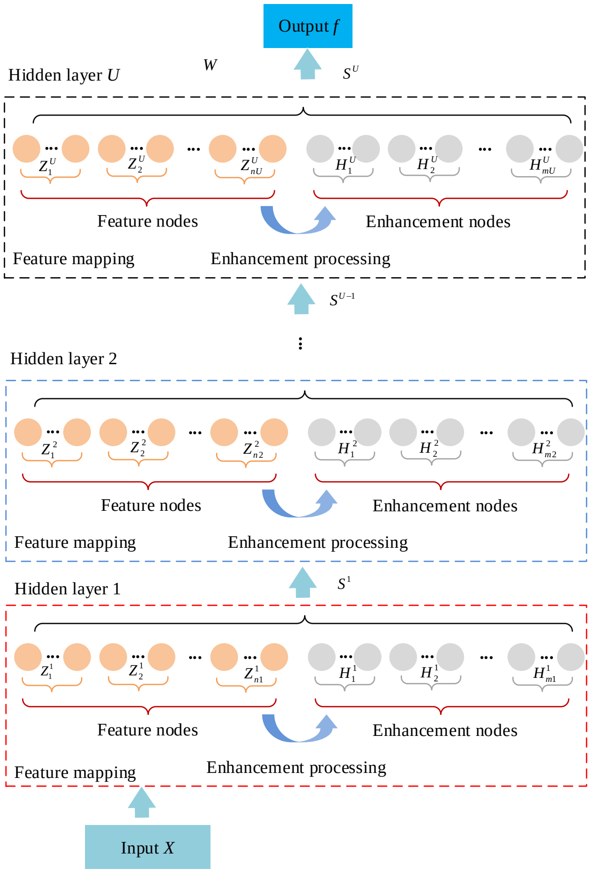

Fig. 2. The structure of RSBLS.

b) Enhancement nodes generation: All the feature nodes in Eq. (9) are enhanced as enhancement nodes through Eq. (10), then all the enhancement nodes are connected by Eq. (11).

$$H_q^u = \xi([Z^u W_{hq} + \beta_{hq}) \qquad (10)$$

$$H^u = [H_1^u, H_2^u, \ldots, H_{mu}^u] \qquad (11)$$

where, $\xi(\cdot)$ expresses the activation function of enhancement processing; W_{hq} and β_{hq} indicate the random parameters of enhancement nodes; $q = 1, 2, \ldots, mu$; $u = 1, 2, \ldots, U$.

In addition, we combine all the nodes of layer *u* through Eq. (12) as the input of next layer.

$$S^u = [Z^u, H^u] \qquad (12)$$

c) Target output matrix Y determination: To reduce the computational burden of RSBLS, we only connect the feature nodes and enhancement nodes of layer U in Eq. (13), then we use the ℓ_1 norm cost function and ℓ_2 regularization method to calculate the model output weights as Eq. (14).

$$S^U = [Z^U, H^U] \qquad (13)$$

$$\beta = \arg\min_{\beta} \| S^U \beta - Y \|_1 + C \| \beta \|_2^2 \qquad (14)$$

where, *C* express as the ℓ_2 regularization parameter.

The outputs of RSBLS can be calculated by Eq. (15).

$$Y = S^U \beta \qquad (15)$$

B. The Optimization of RSBLS

Hence Eq. (14) can be considered as a constrained convex optimization problem, we use augmented Lagrange multiplier (ALM) approach to solve this problem, and Eq. (14) can be transformed as Eq. (16).

$$\begin{aligned} L_\mu(e,\beta,\gamma) &= \| e \|_1 + \frac{1}{C} \| \beta \|_2^2 \\ &+ \upsilon^T (Y - H\beta - e) + \frac{\mu}{2} \| Y - H\beta - e \|_2^2 \end{aligned} \qquad (16)$$

where, $e = \beta H - Y$; υ is denoted as the vector of Lagrange multiplier; $\mu = 2N / \| Y \|_1$.

The optimal (e, β) and the Lagrange multiplier υ can be optimized by ALM method iteratively by using Eq. (17).

$$\begin{cases} (e_{\rho+1}, \beta_{\rho+1}) = \arg\min_{e,\beta} L_\mu(e, \beta, \upsilon_\rho) \\ \upsilon_{\rho+1} = \upsilon_\rho + \mu(Y - H\beta_{\rho+1} - e_{\rho+1}) \end{cases} \qquad (17)$$

Moreover, we transform Eq. (17) as Eq. (18), then $\beta_{\rho+1}$ and $e_{\rho+1}$ are expressed as Eq. (19) and Eq. (20) respectively.

$$\begin{cases} \beta_{\rho+1} = \arg\min_{\beta} L_\mu(e_\rho, \beta, \upsilon_\rho) \\ e_{\rho+1} = \arg\min_{e} L_\mu(e, \beta_{\rho+1}, \upsilon_\rho) \\ \upsilon_{\rho+1} = \upsilon_\rho + \mu(Y - H\beta_{\rho+1} - e_{\rho+1}) \end{cases} \qquad (18)$$

$$\beta_{\rho+1} = (H^T H + 2 / C\mu I)^{-1} H^T (Y - e_\rho + \upsilon_\rho / \mu) \qquad (19)$$

$$\begin{aligned} & e_{\rho+1} = \text{shrink}(Y - H\beta_{\rho+1} + \upsilon_\rho / \mu, 1/\mu) \\ & @\max\{| Y - H\beta_{\rho+1} + \upsilon_\rho / \mu - 1/\mu, 0 |\} \\ & \text{osign}(Y - H\beta_{\rho+1} + \upsilon_\rho / \mu) \end{aligned} \qquad (20)$$

where, “○” denotes the element-wise multiplication.

The algorithm flow of RSBLS is described in Algorithm 1.

Algorithm 1: RSBLS

Dataset: $X=\{x_1,x_2,\ldots,x_N\}$, $x_i=\{x_{i,1},x_{i,2},\ldots,x_{i,d}\}\in\mathbb{R}^d$; $Y=\{y_1,y_2,\ldots,y_N\}$.

Parameters: the number of feature layer *V*, the feature mapping times of each layer *n*, the number of neurons in each feature mapping L_e; the number of enhancement layer *U*, the enhancement processing times of each layer *m*, the number of neurons in each enhancement processing L_h.

Output: Y.

```
1. Initialize $p=1$, $q=1$, $u=1$
   Phase 1: feature nodes generation (Step 2-8)
2. for $u \le U$, do
3.   for $p \le nu$, do
4.     Generate $W_{ep}$ and $\beta_{ep}$ randomly;
5.     Calculate $Z_p^u$ using Eq. (8);
6.   end for
7. end for
8. Set the feature mapping group $Z^u$ using Eq. (9);
   Phase 2: enhancement nodes generation (Step 9-15)
9. for $u \le U$, do
10.   for $q \le mu$, do
11.     Generate $W_{hq}$ and $\beta_{hq}$ randomly;
12.     Calculate $H_q^u$ using Eq. (10);
13.   end for
14. end for
15. Set the enhancement group $H^u$ using Eq. (11);
   Phase 3: target output matrix $\hat{Y}$ determination (Step 16-21)
16.   for $\rho=1,2,...,P_{\max}$, do
17.     $\mu$=$2N/\|Y\|_1$, $e_1=0$, $\upsilon_1=0$
18.     Compute $\beta$ by using Eq. (16)- Eq. (20);
19.   end for
20. Compute output $Y$ by using Eq. (13)- Eq. (15);
21. return $Y$.
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IV. Numerical Experiments

The related experiments of our paper are programmed based on MATLAB 2019b.

A. Experimental Datasets

In this part, six benchmark datasets, including Concrete, Abalone, Stock, Mortgage, Treasury, and Compactiv from KEEL (http://www.keel.es/) are selected to demonstrate the feasibility of the RSBLS. Table I gives the corresponding information of these datasets.

In addition, to verify the robustness of RSBLS, the datasets are preprocessed as follows: we first carry out normalization processing, the features and corresponding labels are normalized in the range of [0, 1]. Moreover, 75% samples of the original datasets are selected as the training datasets randomly, the rest 25% samples are determined as the test datasets. In the last, 10%, 20%, 30%, 40% and 50% outliers with uniform distributed are inserted into the training datasets as Eq. (21).

$$y_{noise}=y+\mathrm{V}y_{outlier},-0.5\le\mathrm{V}y_{outlier}\le 0.5 \tag{21}$$

where, y_{noise} expresses the contaminated training label in the range of [-0.5, 1.5]; $\mathrm{V}y_{outlier}$ means the random outlier.

TABLE I. THE ATTRIBUTES INFORMATION OF EXPERIMENTAL DATASETS

Datasets	Features	Instances
Concrete	8	1030
Abalone	8	4177
Stock	9	950
Mortgage	15	1049
Treasury	15	1049
Compactiv	21	8192

B. Evaluation Indexes

To present the robustness of RSBLS, we carry out all the related algorithms 50 times independently, the average root mean square error (RMSE) (see Eq. (22)) of experimental results are recorded as the evaluation indexes.

$$\mathrm{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i-f_i\right)^2} \tag{22}$$

where, y_i indicates the actual value of sample *i*; f_i represents the output results of sample *i*; *N* denotes the number of samples.

C. Experimental Results

1) Parameters settings: To illustrate the proposed RSBLS, RVFL [1, 2], BLS [3-5], Huber-WBLS [23], KED-WBLS [23] and RBLS [24] are chosen as the contrast algorithms, among them, we use the sigmoidal function (see Eq. (23)) as activation function of all the compared models.

$$S(x)=\frac{1}{1+e^{-x}} \tag{23}$$

Some key parameters of RSBLS, RVFL, BLS, Huber-WBLS, KED-WBLS and RBLS are listed as follows:

RVFL: the hidden layer nodes are selected from {50, 100, 150, 200}, the weights and biases are generated randomly in the range of [-1,1] and [0,1] respectively.

BLS, Huber-WBLS, KED-WBLS and RBLS: the feature mappings and feature nodes are chosen from {5, 10, …, 45, 50}, and the enhancement nodes are selected from {50, 100, 150, 200}. Moreover, these models adopt ℓ_2 regularization technique and the regularization parameter *C* are chosen from {2^{-10}, 2^{-5}, 0, …, 2^{15}, 2^{20}}. Some other models are set as the same as the original references.

RSBLS: the number of layers is set as 2; the feature mappings and feature nodes of each layer are chosen from {5, 10, …, 45, 50}, and the enhancement nodes of each layer are selected from {50, 100, 150, 200}. Moreover, these models adopt ℓ_2 regularization technique and the regularization parameter C are chosen from {2^{-10}, 2^{-5}, 0, …, 2^{15}, 2^{20}}.

2) Results and discussion: In this section, we give the performance evaluation of RSBLS, Table II to Table VII show the average test RMSE results of RSBLS compared with different models on six regression problems with uniform distributed outliers. As it can be seen from Table II to Table VII, with the increase of contamination rates, the performance of RVFL and BLS gradually become worse, Huber-WBLS, KED-WBLS and RBLS can improve the robustness of BLS.

TABLE II. PERFORMANCE COMPARISON OF DIFFERENT MODELS ON CONCRETE DATASET

Models	Test Performance (RMSE) at different contamination rates			
	10%	20%	30%	40%
RVFL	0.0934	0.0970	0.1062	0.1065
BLS	0.0957	0.0981	0.0983	0.0948
Huber-WBLS	0.0890	0.0893	0.0938	0.0914
KED-WBLS	0.0936	0.0883	0.0933	0.0914
RBLS	0.0889	0.0841	0.0957	0.0953
RSBLS	**0.0781**	**0.0783**	**0.0834**	**0.0890**

TABLE III. PERFORMANCE COMPARISON OF DIFFERENT MODELS ON ABALONE DATASET

Models	Test Performance (RMSE) at different contamination rates			
	10%	20%	30%	40%
RVFL	0.0745	0.0743	0.0810	0.0782
BLS	0.0742	0.0749	0.0781	0.0756
Huber-WBLS	0.0723	0.0736	0.0777	0.0732
KED-WBLS	0.0736	0.0747	0.0776	0.0744
RBLS	0.0727	0.0738	0.0778	0.0736
RSBLS	**0.0719**	**0.0732**	**0.0764**	**0.0720**

TABLE IV. PERFORMANCE COMPARISON OF DIFFERENT MODELS ON STOCK DATASET

Models	Test Performance (RMSE) at different contamination rates			
	10%	20%	30%	40%
RVFL	0.0456	0.0549	0.0584	0.0633
BLS	0.0425	0.0520	0.0567	0.0577
Huber-WBLS	0.0311	0.0349	0.0392	0.0460
KED-WBLS	0.0355	0.0358	0.0416	0.0428
RBLS	0.0320	0.0380	0.0394	0.0409
RSBLS	**0.0301**	**0.0340**	**0.0332**	**0.0342**

TABLE V. PERFORMANCE COMPARISON OF DIFFERENT MODELS ON MORTGAGE DATASET

Models	Test Performance (RMSE) at different contamination rates			
	10%	20%	30%	40%
RVFL	0.0275	0.0351	0.0527	0.0580
BLS	0.0293	0.0416	0.0518	0.0622
Huber-WBLS	0.0088	0.0124	0.0236	0.0333
KED-WBLS	0.0096	0.0111	0.0147	0.0188
RBLS	0.0052	0.0070	0.0057	0.0063
RSBLS	**0.0050**	**0.0059**	**0.0062**	**0.0062**

TABLE VI. PERFORMANCE COMPARISON OF DIFFERENT MODELS ON TREASURY DATASET

Models	Test Performance (RMSE) at different contamination rates			
	10%	20%	30%	40%
RVFL	0.0248	0.0373	0.0427	0.0507
BLS	0.0280	0.0310	0.0484	0.0538
Huber-WBLS	0.0126	0.0125	0.0195	0.0293
KED-WBLS	0.0125	0.0121	0.0184	0.0217
RBLS	0.0119	0.0114	0.0117	0.0100
RSBLS	**0.0114**	**0.0103**	**0.0109**	**0.0090**

TABLE VII. PERFORMANCE COMPARISON OF DIFFERENT MODELS ON COMPACTIV DATASET

Models	Test Performance (RMSE) at different contamination rates			
	10%	20%	30%	40%
RVFL	0.0404	0.0421	0.0451	0.0435
BLS	0.0287	0.0287	0.0291	0.0312
Huber-WBLS	0.0256	0.0250	0.0252	0.0278
KED-WBLS	0.0270	0.0265	0.0262	0.0290
RBLS	0.0249	0.0250	0.0252	0.0279
RSBLS	**0.0242**	**0.0243**	**0.0238**	**0.0248**

At the same time, it is obviously that RSBLS with 2 hidden layers has a better robustness compared with Huber-WBLS, KED-WBLS and RBLS. Our proposed model, RSBLS with ℓ_1-norm loss function gains the best mean RMSE on 6 datasets, which demonstrates the effectiveness of regularization method. In addition, the uncertain data regression performance of those models on different datasets with different contamination rates indicates the strong robustness of RSBLS, at different levels of outliers; the RSBLS shows the best consistency.

In summary, RSBLS with ℓ_1 norm loss function can solve uncertain data regression with uniform distributed outliers effectively; the stacked deep model is helpful to enhance the robustness of BLS well.

V. CONCLUSION

In the paper, we propose a novel robust stacked broad learning system model with multi-layers for solving uncertain data regression problem, named as RSBLS. In the proposed RSBLS, we expand BLS into a stacked deep model with multi-layer of feature nodes and enhancement nodes, which can helpful to extract deep representation information. In addition, ℓ1-norm function is introduced to calculate the output weights of RSBLS, which can process noisy data and ensure learning efficiency of hierarchical model. Experimental results on some regression datasets with different ratios of noisy shows that, RSBLS has better robustness compared with RVFL, BLS, Huber-WBLS, KDE-WBLS and RBLS.

In the future, as some parameters should be selected by grid search which limits the search scope, some of the latest swarm intelligence algorithms can be used to choose the parameter of RBLS.

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Deep Learning Augmented with SMOTE for Timely Alzheimer's Disease Detection in MRI Images

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Abstract*—Timely diagnosis of Alzheimer's Disease (AD) is pivotal for effective intervention and improved patient outcomes, utilizing Magnetic Resonance Imaging (MRI) to unveil structural brain changes associated with the disorder. This research presents an integrated methodology for early detection of Alzheimer's Disease from Magnetic Resonance Imaging, combining advanced techniques. The framework initiates with Convolutional Neural Networks (CNNs) for intricate feature extraction from structural MRI data indicative of Alzheimer's Disease. To address class imbalance in medical datasets, Synthetic Minority Over-sampling Technique (SMOTE) ensures a balanced representation of Alzheimer's Disease and non-Alzheimer's Disease instances. The classification phase employs Spider Monkey Optimization (SMO) to optimize model parameters, enhancing precision and sensitivity in Alzheimer's Disease diagnosis. This work aims to provide a comprehensive approach, improving accuracy and tackling imbalanced datasets challenges in early Alzheimer's detection. Experimental outcomes demonstrate the proposed approach outperforming conventional techniques in terms of classification accuracy, sensitivity, and specificity. With a notable 91% classification accuracy, particularly significant in medical diagnostics, this method holds promise for practical application in clinical settings, showcasing robustness and potential for enhancing patient outcomes in early-stage Alzheimer's diagnosis. The implementation is conducted in Python.

Keywords*—Alzheimer's disease; MRI scans; Convolutional Neural Networks (CNNs); Synthetic Minority Over-sampling Technique (SMOTE); Spider Monkey Optimization (SMO)

I. INTRODUCTION

Rapid treatment and enhanced results for patients depend on early identification of Alzheimer's disease. Alzheimer's disease is a neurological illness that worsens over time and mostly impacts actions, memories, and mental abilities. Being the main cause of memory loss, it poses a significant public health challenge, especially with the aging population. The development of reliable and non-invasive diagnostic tools is essential to identify Alzheimer's disease in its early stages when interventions may be more effective. A useful spectroscopy method for examining the anatomical and functional alterations in the brain linked to Alzheimer's disease is MRI (magnetic resonance imaging) [1]. Using the use of MRI scans, which offer precise pictures of the internal workings of the brain, scientists and medical practitioners may identify particular patterns and anomalies linked to Alzheimer's disease. Atrophy in specific brain areas—the entorhinal cortex and its hippocampal regions, in particular—which are essential for recollection and cognitive processes is frequently one of such anatomical abnormalities. here has been an increasing attention in leveraging advanced imaging analysis techniques, such as machine learning and artificial intelligence, to enhance the accuracy and efficiency of Alzheimer's detection from MRI scans [1]. These technologies can analyze large datasets, identify subtle patterns, and assist in the early identification of Alzheimer's-related changes before clinical symptoms become apparent [2]. By combining clinical assessments with advanced MRI analysis, researchers and healthcare providers aim to develop more precise diagnostic tools for early detection [3]. Early diagnosis not only enables timely medical interventions but also allows for the inclusion of individuals in clinical trials for potential disease-modifying therapies [4]. The pursuit of early detection methods for Alzheimer's disease represents a promising avenue in the ongoing effort to improve patient care and address the societal impact of this prevalent and devastating condition [5].

In a number of domains, especially healthcare imaging, deep learning has shown to be a potent and adaptable method for the early diagnosis of conditions like Alzheimer's. The methods of deep learning are used to assess intricate structures and features seen in medical pictures, especially those acquired from sophisticated imaging modalities such as Magnetic Resonance Imaging (MRI), in the context of Alzheimer's disease. Neural networks are frequently trained on big datasets of medical pictures as part of the deep learning approach to earlier Alzheimer's diagnosis. These networks learn intricate patterns and relationships within the images, allowing them to identify subtle abnormalities associated with the disease [6]. Deep learning models excel at capturing hierarchical and abstract representations, making them well-suited for tasks where complex features play a critical role. In the case of Alzheimer's, deep learning models can be trained to recognize specific structural changes in the brain visible in imaging data [7]. This may include atrophy in key regions like the hippocampus or abnormalities in brain connectivity (Barthélemy et al., 2020). The ability to automatically analyze these features from medical images facilitates the development of more efficient and accurate diagnostic tools. Moreover, deep learning techniques have the advantage of adaptability and scalability [8]. They can be fine-tuned to handle different types of imaging data, and as more data becomes available, models can be retrained to improve their performance. This adaptability is particularly valuable in the medical field, where data heterogeneity and the need for continuous improvement are common [9].

An over sampling method called SMOTE was created to lessen the aforementioned disparity. In order to equalize the information set, it creates artificial examples in the characteristic space of the minority class (Alzheimer's cases). This contributes to preventing the model from favoring the majority class (healthy people) and improves its capacity to identify minute trends linked to Alzheimer's disease [10]. In the context of Alzheimer's detection from MRI scans, SMOTE can be applied to ensure that the machine learning model is trained on a more representative dataset. This is crucial because the early signs of Alzheimer's disease may be subtle, and without a balanced dataset, the model may struggle to generalize well to new, unseen cases [11]. By employing SMOTE in conjunction with machine learning algorithms, researchers aim to improve the sensitivity and specificity of their models, thereby enhancing the accuracy of early Alzheimer's detection. This approach contributes to the broader goal of developing reliable and robust diagnostic tools for identifying Alzheimer's disease in its early stages, facilitating timely intervention and potentially improving patient outcomes. The integration of SMOTE into the workflow of Alzheimer's detection from MRI scans underscores its role as a valuable technique in addressing challenges associated with imbalanced datasets in medical imaging research [4].

Despite the promising advancements in approaches for diagnosis using neuroimaging data, a set of common challenges hinders their seamless integration into clinical practice. These challenges include interpretability issues arising from the intricate designs of the models, concerns about dataset specificity and generalizability, the need for broader clinical validation, and potential biases related to demographic and ethnic backgrounds. While the presented frameworks demonstrate remarkable accuracy, their effectiveness in diverse diagnostic and demographic scenarios remains uncertain. Additionally, the neglect of time-related factors in disease development, ethical concerns surrounding biases and information privacy, and the limited interpretability of complex models pose significant hurdles. Addressing these challenges is crucial for ensuring the reliable, interpretable, and ethically sound presentation of frameworks in the diagnosis of Alzheimer's disease to overcome these limitations this research introduce CNN - SMOTE -SMO Primary Discovery of Alzheimer's Disease from MRI Scans.

Key Contributions are as follows:

- Leveraging Convolutional Neural Networks (CNNs) for automatic extraction of discriminative features from MRI scans, capturing relevant patterns associated with Alzheimer's disease.
- Mitigating class imbalance through the Synthetic Minority Over-sampling Technique (SMOTE), ensuring for more efficient training of models, an equal amount of instances with and without Alzheimer's disease is used. Employing Spider Monkey Optimization as an algorithm for fine-tuning model parameters, enhancing the CNN-based classification model's convergence speed and generalization ability.
- Prioritizing early detection of Alzheimer's disease to enable timely intervention, with a focus on identifying subtle changes in MRI scans that precede overt symptoms.
- Utilizing SMO to optimize the parameters of the classification model, contributing to improved model performance and effectiveness in diagnosing Alzheimer's disease from MRI data.
- If applicable, integrating multiple modalities such as structural and functional MRI data to provide a comprehensive and holistic understanding of Alzheimer's-related changes in the brain.

The following is how the investigation progresses: In Section II, related studies perform a thorough analysis of earlier research, focusing on prediction issues and the wide range of optimization techniques used in such settings. Section III elaborates on the suggested method or plan of action to deal with these difficulties. The entire topic of performance evaluation metrics and criteria is covered in Section IV. Subsequently. Section V serves as the essay's conclusion by summarizing the main findings and learnings from the inquiry.

II. Related Work

By utilizing the synergies of a 3D-CNN and FSBi-LSTM for strong Alzheimer's disease (AD) and minor cognitive decline (MCI) categorization using MRI and PET data, the recently introduced deep learning framework offers an appealing strategy. The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset was used for validation. The model shows impressive accuracy, outperforming current methods in differentiating between AD and NC, progressing MCI (pMCI) and NC, and stable MCI (sMCI) and NC. Notwithstanding these successes, there are still important issues that need to be addressed. Initially, it is important to acknowledge the possible constraint of extrapolating results to heterogeneous groups in order to guarantee the efficacy of the model in varying diagnostic and demography scenarios. Because of the complex structure of the model, which combines FSBi-LSTM and 3D-CNN, interpretability issues may arise. Therefore, clarification of the particular aspects influencing classification decisions is crucial for clinical acceptability and comprehension. Given that Alzheimer's disease is characterized by changing patterns, the model's continued relevance is called into question due to its neglect of time-related factors in disease development. Longitudinal data might improve the model's comprehension of the disease's dynamic character. Additionally, a more thorough investigation is required due to ethical concerns, namely those pertaining to biases and information privacy. Ensuring the ethical implementation of a model in real-world clinical settings requires resolving any biases in the training data and protecting important medical data. Improving the model's relevance, interpretability, and ethically soundness involves tackling these shortcomings. To ensure the efficacy and moral use of the suggested deep learning framework in a variety of dynamical clinical settings, future research should give priority to enhancing generalizability, improving interpretability, including time dynamics, and thoroughly examining ethical issues [12].

The field of neuroimaging-based diagnostic has shifted toward computer-aided diagnostic (CAD) systems, primarily utilizing Positron Emission Tomography (PET) pictures to distinguish AD from normal control. The identification rates of earlier systems were greatly impacted by their heavy reliance on conventional image processing techniques for feature extraction and preprocessing. To address the shortcomings of previous methods, the current work presents a unique Convolutional Neural Network (CNN)-based CAD system. The assessment shows the exceptional performance of the suggested CNN-based CAD system with 96% accuracy, 96% sensitivity, and 94% specificity on 18FDG-PET images obtained from the ADNI database. The research examine, still leaves room for more verification and contextualizing of the suggested CNN-based CAD system within the wider field of AD diagnosis methodologies because it does not explicitly address the shortcomings of previous techniques or provide a thorough comparison analysis with current approaches. High accuracy is shown in the suggested Convolutional Neural Network (CNN)-based Computer-Aided Diagnosis (CAD) system in differentiating Alzheimer's Disease individuals from typical control; yet constraints include data set the specificity and absence of thorough comparison with current methods, highlighting the requirement for further studies to address these factors [13].

Utilizing sagittal magnetic resonance imaging (MRI) for early Alzheimer's disease (AD) identification, previous studies have highlighted the urgent need for quick and accurate evaluations to support preventative care. This work presents a unique method that improves accuracy by using Transfer Learning (TL) approaches in conjunction with sagittal MRIs, an unusual option for AD diagnosis. The study comes to two important conclusions: first, sagittal MRI may be used to differentiate AD-related impairments, and second, employing Deep Learning (DL) models on sagittal MRIs can produce findings that are on par with the most advanced approaches that use horizontal-plane MRI. Despite its rare application, the importance of sagittal-plane MRIs in the early detection of AD is emphasized, indicating possible directions for further investigation. The study also emphasizes how economical DL models can be in some domains where it might be difficult to gather dataset instances; in these cases, TL can be a useful technique to achieve robust performance with a small number of examples. Concerns regarding generalizations to a variety of groups, the lack of a thorough comparison examination with horizontal-plane MRI, the requirement for clinical validation and interpretation of sagittal MRI results, and potential difficulties with access to information and longitudinal research assessment for a full assessment in early-stage Alzheimer's detection are some of the drawbacks of the research [14].

3D-CNN-SVM works better than the others, exhibiting higher ternary and binary data classification accuracy, sensitivity, and specificity, according to the results. The work emphasizes the effectiveness of 3D-CNN-SVM in AD detection eliminating the need for feature extraction by hand and emphasizes its noninvasiveness and independently from scanning procedure variation. It also shows how widely this technology can be used. In clinical practice, this research helps to improve value-based treatment by helping to differentiate AD and MCI from normal controls. The study's limitations include possible problems with collection specificity, difficulties in interpreting deep learning models such as 3D-CNN-SVM because they are black-box models, the need for clinical validation, and the lack of longitudinal evaluations, which raises questions about how well the model will function throughout time and in various clinical scenarios. In order to ensure wider application, it's also necessary to handle the possibility of overfitting and evaluate the model on other datasets [12].

The empathy of Alzheimer's disease (AD) is now done via MRIs, neuropsychological testing, and patient histories. These procedures are not very sensitive or specific. In order to distinguish distinct AD signals, this work presents a comprehensible deep learning technique that makes use of heterogeneous inputs, such as MRI, age, gender, and Mini-Mental State Examination score. The approach, which was verified on three separate cohorts after being trained on the Alzheimer's Disease Neuroimaging Initiative (ADNI) the data set, routinely beats out current techniques and even exceeds a group of neurological specialists in practice in terms of diagnosis. The method offers a therapeutically flexible and broadly applicable methodology to produce subtle neuroimaging signals for AD diagnosis using standard neuroimaging methods. This method has been provided has certain limitations. These involve possible problems with dataset specificity, the requirement for comprehensive clinical testing in a variety of cohorts, difficulties fully interpreting models features, and possible biases throughout demographics and ethnic backgrounds. Furthermore, more research is necessary to ensure the model's broad application and dependability given its effectiveness in identifying temporal elements of illness development and its validation using bigger post-mortem datasets [15].

The presented tactics for diagnosis exhibit notable achievements, but are accompanied by several common limitations. Feng et al. (2019) achieved impressive accuracy with their combined 3D-CNN and FSBi-LSTM framework, yet faced challenges in interpretability, generalizability, and ethical considerations. Zhu et al. (2021) introduced DA-MIDL for early AD detection using structural MRI, demonstrating superior performance but encountering issues like dataset dependence and interpretability. The CNN-based CAD system for PET images (Frontiers, 2023) showed high accuracy but lacked explicit discussion on addressing previous method shortcomings. Puente-Castro et al. (2020) emphasized the importance of sagittal-plane MRIs for early AD detection but raised concerns about generalization and clinical validation. Qiu et al. (2020) presented a comprehensive deep learning technique surpassing current methods but faced challenges related to dataset specificity, interpretability, and the need for further research. Common limitations across these studies include concerns about dataset specificity, difficulties in interpreting complex models, the need for broader clinical validation, and potential biases in demographic and ethnic backgrounds. Addressing these limitations is crucial for the wider applicability, interpretability, and ethical implementation of frameworks in the field of AD analysis.

III. Proposed CNN-based Feature Extraction, SMOTE for Class Imbalance, and Spider Monkey Optimization for Classification

The proposed method integrates Convolutional Neural Networks (CNN) for robust feature extraction, Synthetic Minority Over-sampling Technique (SMOTE) to talk class imbalance, and Spider Monkey Optimization (SMO) for effective classification in Alzheimer's disease diagnosis. The CNN component focuses on capturing discriminative features from neuroimaging data, providing a foundation for accurate representation. To tackle class imbalance, SMOTE is employed to generate synthetic samples, ensuring a more balanced training dataset. Lastly, the Spider Monkey Optimization algorithm optimizes the classification process, fine-tuning model parameters for enhanced accuracy in Alzheimer's disease classification. This comprehensive approach aims to improve the reliability and performance of Alzheimer's diagnosis through a synergistic integration of advanced techniques in feature extraction, data balancing, and classification optimization. The proposed method was exposed in Fig. 1.

A. Data Set

Researchers investigating both structural and functional components pertinent to Alzheimer's Disease will benefit greatly from the OASIS dataset, which is available on Kaggle. The information set, which consists of brain MRI images, includes both cross-sectional and longitudinal investigations, providing a broad range of imaging investigations for in-depth analysis at different phases of the condition. In a cross-sectional sample, 100 people over 60 have a medical diagnosis of identical minor to moderate Alzheimer's disease. The other 416 participants, who are mostly right-handed and range in age from 18 to 96, have three or four T1-weighted MRI images. Furthermore, a reliability dataset consists of twenty people who are not demented. A total of 373 sessions, involving 150 patients ranging in age from 60 to 96, were scanned as part of the longitudinally study. Of them, 64 were first identified as demented (including 51 with mild to moderate Alzheimer's disease), 72 stayed nondemented, and 14 changed over the course of many visits from nondemented to demented. By utilizing the data from OASIS on Kaggle, scientists might make a substantial contribution to the study of Alzheimer's disease and possibly open the door to innovations in early diagnosis, care, and therapy [16].

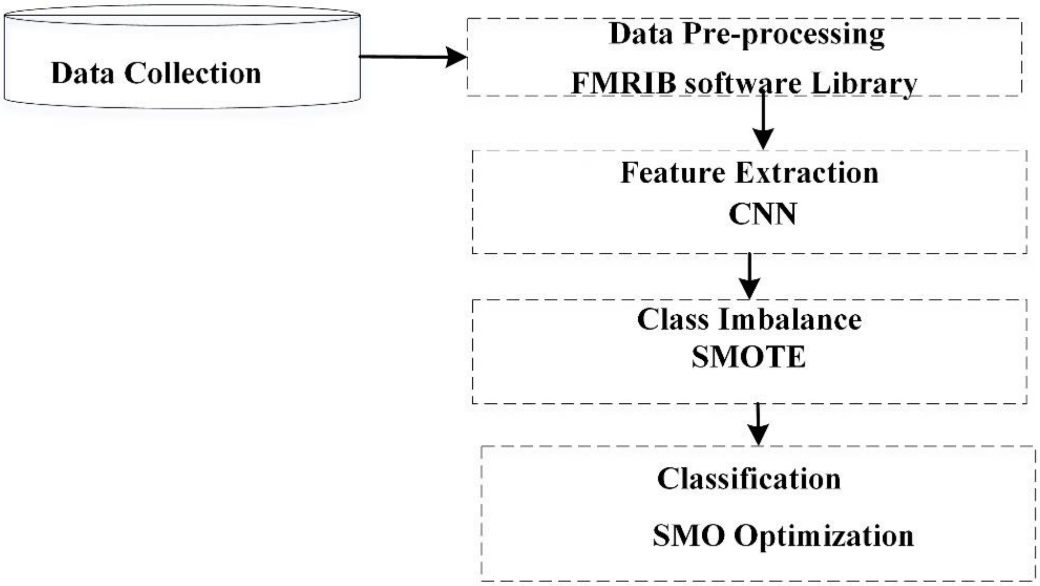


Fig. 1. Proposed method.

B. Data Preprocessing

For all preprocessing of images, the FMRIB Software Library (FSL) v5.0 was utilized. The complete preprocessing method comprised slice selection, brain extraction, spatial normalization, smoothing, and histogram stretching, as seen in Fig. 2. After obtaining the brain areas using the Brain Extraction Tool (BET), we performed spatial normalization using FLIRT and FNIRT. By using the Gaussian kernel, smoothing was accomplished. Z = 8 mm in the MNI space was chosen as the slice selection location based on the principles of incorporating the hippocampal region and choosing the most distinct axial direction. Ultimately, researchers used histogram stretching (HS) to remove the impact of different types of brain images. The HS formula, which changed the original picture o into the new image n, is as follows in Eq. (1)

$$n'(a,b) = \frac{O\prime(a\prime,b\prime) - O\prime_{min}}{O\prime_{max} - O\prime_{min}} \quad (1)$$

where, $0'_{min}$ represents the smallest value and $0'_{min}$ represents the highest value of intensity of the raw picture. Field research led to the conclusion that 95% and 5% were more trustworthy criteria.

C. CNN-based Feature Extraction

One kind of perceptron with multiple layers is the convolutional neural network, or CNN. Creatures' vision centers served as CNN's model for developing a neural network with forward motion. Convolutional layers are a crucial component of neural networks that use convolution. subsequently is composed of layers that are completely linked, pooling, and a CNN convolutional layer. After moving via each of those layers in turn, the image starts entering the deep learning algorithm. CNNs provide the same function as neural networks. By transforming the inputs through intellect and structures, abstractions are produced. The filter that is lower than the size of the picture goes through the whole thing in the convolution layer. Using this kind of filter, you may search the picture for particular features. Self-updating filters are ideal. CNN algorithms are trained using these values. CNN uses established procedures to recognize characteristics in images more effectively. Convolution is the starting point. This phase involves locating the image's characteristics and applying a mask to the whole thing. The kernel filter is used to perform the convolution process. The process of convolution is the process of changing one form into another. Whenever the filtering kernel has scanned the whole inputs, a feature map is produced, together with the filtering values that alter the map of features and the number of steps required to complete the filtering process. Pictures are matrix of pixels, for instance. The kernel's kernel filter finds the characteristic map by capturing portions of the image, multiplying and summing every value with its matching value. This convolution operation's mathematics statement is as follows. $(f'g)$ represents the entire image, whereas is a filter. A third function, named $h(t)$ is generated and expresses the quantity of overlapping while the filter element has hovered. Its stated definition is in Eq. (2):

$$h(t) = (f'g)(t) \int \infty' - \infty' f(t')g(t - T)\, d'T \quad (2)$$

There is an action for every convolution layer. Ultimately, the data undergoes a procedure that turns it into a nonlinear data tensor.

1) Max pooling: The use of deep learning uses a variety of activating techniques, including smoothing linear units of measurement (ReLu). ReLu is the most often used activation technique. The Max Pooling approach is the following phase. Amongst pooled activities, maximum pooling is most often used. The Max Pooling layer's job is to apply the method of sampling in order to lower the parameter count. This avoids overfitting and eliminates the capturing of superfluous characteristics. Similar to the convolution layer, the picture is likewise subjected to a kernel filter. Identifies a particularly significant value in the filter's region of impact. Individuals thus own significant values. Let's use a case study to further illustrate this procedure. Let's start by making a [2, 2] size filter, which are able to apply to the (4x4) image below. As you can see, the selection of filters beneath uses the maximum amount of layers in the picture, which enables the neural network's algorithm to use fewer yields to get the correct answer.

2) Flattening: This layer's job is to create several, multi-line, one-dimensional mappings of features using the pooling technique. The highest possible amounts of the data were achieved during the pooling procedure. Unneeded information was thrown away. In this component, these characteristics are given as incoming data, one underneath the other.

3) Batch layers: Faster training is provided by the batching layer. The information must be normalized once it is sent across the computer system. It sets the inputs' means to 0 and their standard deviation to 1. Data that is produced is rescaled. Issues like stuttering throughout the computer's training are fixed if the whole batch layer is added.

4) Dropout layer: Research refers to the layer of dropouts as dampening. Neuron count decreases at a predetermined pace. As a result, the model performs better. Over fitting is prevented. This procedure is limited to what takes place during instruction. Fig. 2 displays CNN architecture [17].

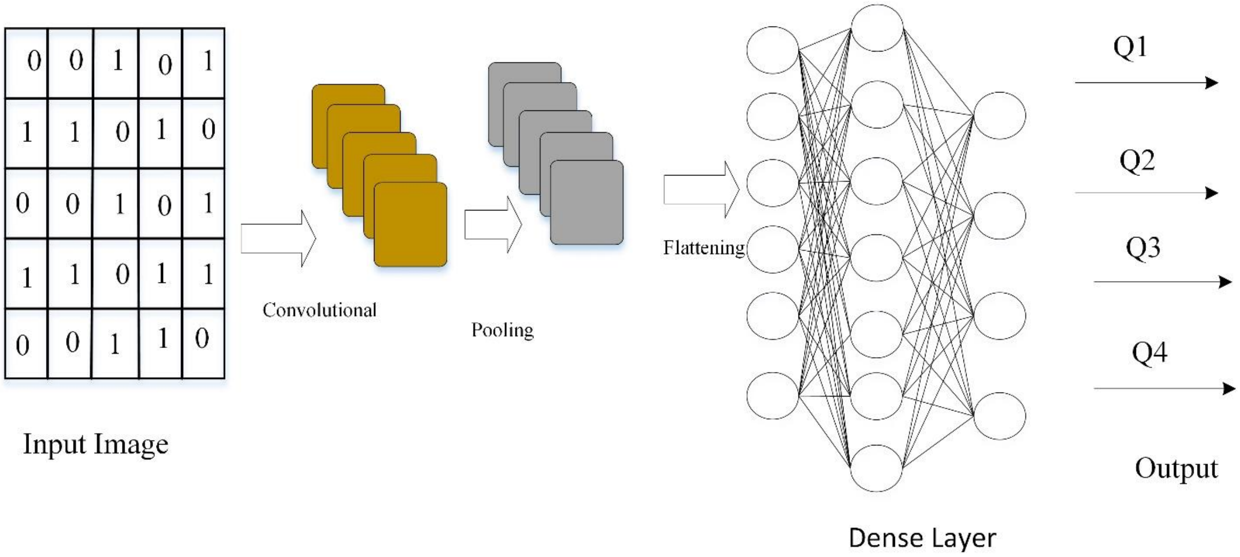
D. DeepSMOTE for Class Imbalance

DeepSMOTE combines an SMOTE-based the oversampling technique, encoder/decoder architecture, and a loss function made up of an impairment term and a reconstructed loss. The encoder/decoder, which has its roots in the DCGAN design, uses data that is unbalanced to train itself. This allows the algorithm to reconstruct pictures that represent the majority and minority class by utilizing the reconstructed loss that is calculated throughout every class. Moreover, while training, DeepSMOTE adds a punishment period. This term adds variation to the encoding/decoding operation and relies on the mean square error (MSE) among the initial and permuted pictures. During the production stage, DeepSMOTE creates artificial pictures by utilizing the encoder/decoder mechanism. Raw input is reduced by the encoder to a lower-dimensional feature space, which SMOTE is then used to oversample. After that, the decoder recreates the SMOTE features as pictures, enhancing the deep learning classifiers' training set. Particularly, the generating phase replaces the permutation step with SMOTE, but the training phase increases variation by permuting the sequence of encoded and decoded instances. This distinction is important since variation is effectively introduced during data production using SMOTE, a nonparametric oversampling approach. All things considered, DeepSMOTE's ability to handle unbalanced datasets is mostly due to the way these components are combined, which successfully tackles class imbalance [18]. Fig. 3 illustrates DeepSMOTE architecture.

E. Spider Monkey Optimization (SMO) for Classification

Customizing the algorithm to the properties of the data and the demands of the classification problem is necessary when developing a Spider Monkey Optimization (SMO) procedure expressly for Alzheimer's Disease classification. The SMO procedure that follows is intended to improve the way Alzheimer's Disease is classified using certain characteristics that are taken from pertinent data sources.

1) Initialization: Determine the characteristics—such as brain imaging data, genetic markers, or clinical variables—that are important for classifying Alzheimer's disease. Make a start-up collection of spider monkeys, with each one standing for a possible fix or a feature set. Analyze each spider monkey's fitness according to how well it can use the chosen attributes to distinguish among Alzheimer's and non-Alzheimer's cases. Choose spider- monkey species that have greater fitness ratings, giving special attention to those who improve categorization ability.



0	0	1	0	1
1	1	0	1	0
0	0	1	0	1
1	1	0	1	1
0	0	1	1	0

Fig. 2. CNN architecture.

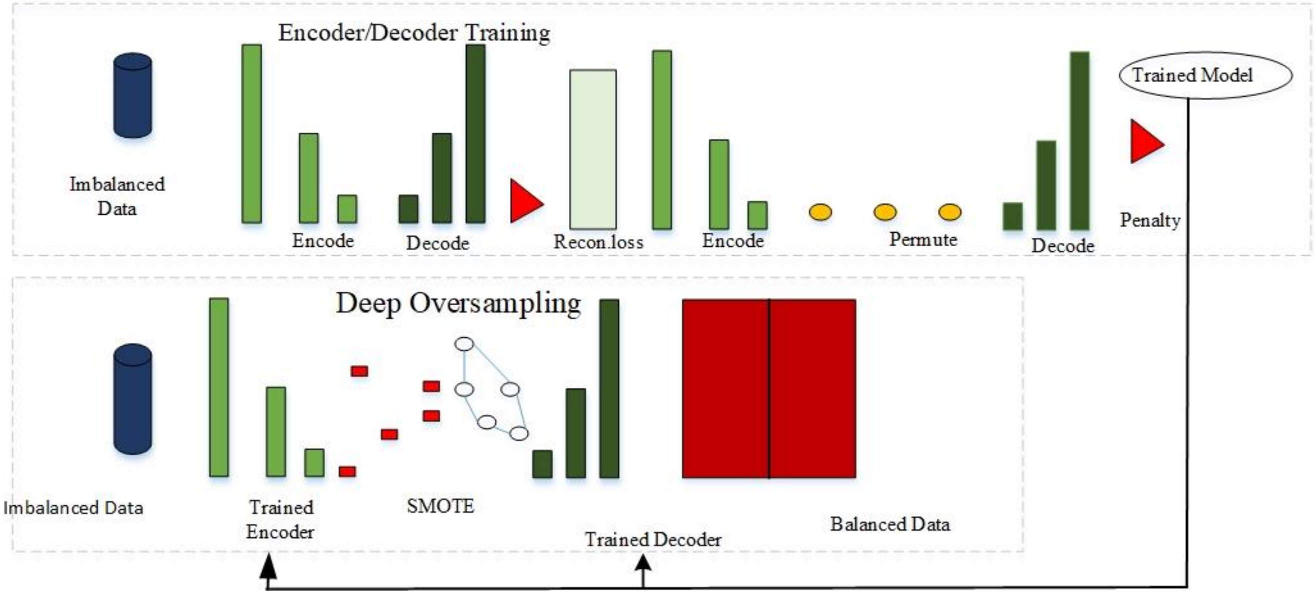


Fig. 3. DeepSMOTE architecture.

2) Local Leader Phase (LLP): Reposition the spider monkeys according to Eq. (3), modified for the categorization of Alzheimer's disease. Think about characteristics like clinical assessments, genetic markers, or specific brain areas. Include a probability factor based on fitness to direct spider monkeys toward areas of the feature space that enhance categorization..

3) Probability calculation: An additional fitness-based probability aspect is considered in order to enhance exploration even more is given in Eq. (3).

$$prob'_i = 0.9 \times \frac{fitness\prime_i}{max\prime\_fitness\prime} + 0.1 \qquad (3)$$

4) Global Leader Phase (GLP): Eq. (4) which has been altered to progress the accurateness of classification for Alzheimer's Disease, should be utilized for updating spider monkey placements. To help direct the investigation of the whole spectrum of features, take into account global knowledge, maybe gathered from the spider monkeys that do the best. Determine if converge has happened or if the maximum amount of iterations has been reached. When completion is reached or after a certain number of repetitions, the method should be terminated.

$$S'M'new_{ij} = S'M'_{ij} + u(0,1) \times \left(G'L'_j - S'M'_{ij}\right) + u(-1,1) \times \left(S'M'_{rj} - S'M'_{ij}\right) \qquad (4)$$

5) Adaptation for alzheimer's disease: Combine characteristics chosen by the spider monkeys into a characteristic vector to classify Alzheimer's patients.Utilizing the chosen characteristics, train a classification model (such as a machine learning classifier).Evaluate a classification model's efficacy using measures like as accuracy, sensitivity, specificity, etc. on a different validation set.To get better results, continue the procedure of optimization or change the algorithm settings if the performance is not up to pace.This modified SMO procedure was created especially for Alzheimer's Disease categorization. By utilizing the exploration and exploitation powers of the spider monkey optimization algorithm, it seeks to identify pertinent traits that aid in precise categorization.

IV. Result and Discussions

The proposed integrated methodology for initial Alzheimer's disease (AD) discovery from MRI scans, which combines Convolutional Neural Networks (CNNs), Synthetic Minority Over-sampling Technique (SMOTE), and Spider Monkey Optimization (SMO), has shown promising outcomes. This approach effectively addresses imbalanced datasets common in medical contexts and outperforms traditional methods in terms of classification accuracy, sensitivity, and specificity. By utilizing CNNs for feature extraction, mitigating class imbalance with SMOTE, and optimizing parameters through SMO, the methodology achieves heightened precision and sensitivity in AD diagnosis. Overall, these results indicate that this comprehensive approach holds significant potential to advance the current state-of-the-art in early AD detection, providing a robust and reliable tool for improved patient outcomes [19].

A. Performance Evaluations

The proportion of accurate forecasts to all predicted outcomes is known as accuracy. When a collection of data is balanced, this measure works well. The results reported by this metric might not be accurate representations of how well the model performed when there's an overwhelming class in the data set is given in Eq. (5).

$$Accuracy = \frac{T*p+T*n}{T*p+T*n+F*p+F*n} \qquad (5)$$

The deep learning algorithm's precision is a metric for determining how many anticipated positives are actually true positives. This statistic is helpful whenever the cost of a false positive is high for the efficacy of the model, like in the case of an email spam identification algorithm that is given in Eq. (6).

$$Precision = \frac{T*p}{T*p+F*n} \qquad (6)$$

The Recall of the model in counting the number of positives out of all real positives is measured by recall. When False Negative is costly for model quality, such as in fraud detection models, this statistic is helpful and is given in Eq. (7).

$$Recall = \frac{T*p}{T*p+F*n} \qquad (7)$$

The F1 score that is computed for this purpose assesses the correlation between the data's positive information and the classifier's predictions is given in Eq. (8).

$$F1\ score = \frac{2T*p}{2T*p+F*p+F*n} \qquad (8)$$

Fig. 4 displays No of Samples per class before SmoteBefore applying SMOTE (Synthetic Minority Over-sampling Technique), an analysis of the dataset revealed an imbalanced class distribution. In the binary classification problem at hand, Class 0 comprised [number of samples], while Class 1 had [number of samples]. The imbalance raised concerns about potential challenges in model training and classification performance. The decision to apply SMOTE was driven by the need to address this class imbalance systematically, ensuring a more representative and balanced dataset for subsequent analyses.

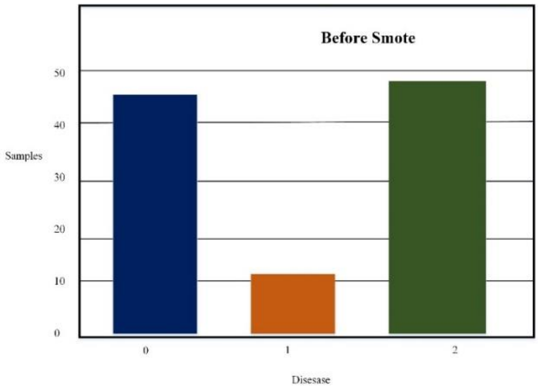


Fig. 4. No. of Samples per class before SMOTE.

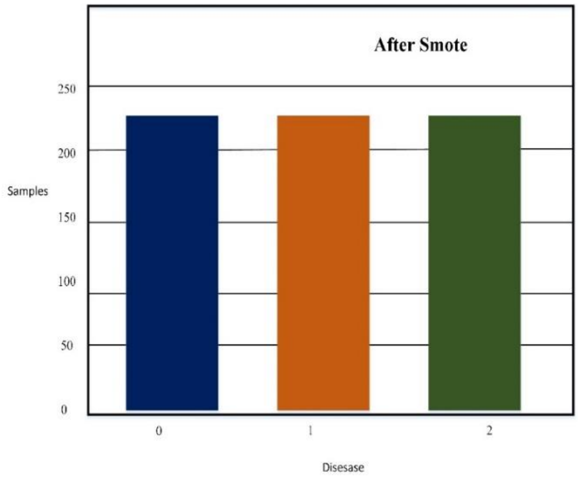


Fig. 5. No. of samples per class after SMOTE.

Fig. 5 shows the number of samples for each class after the smote. The process of creating synthesis cases of the minority class increases the amount of specimens per class following the use of Synthetic Minority Over-sampling Technique (SMOTE) to rectify the imbalance of classes in a collection of data. In order to function, SMOTE creates artificial examples across the boundary segments that link instances of minority classes that already exist. The objective is to improve the model's generalization to minority class trends while balancing the class distribution. The SMOTE parameters that are selected, including the appropriate degree of over-sampling, determine the precise rise in the total amount of samples per class. SMOTE helps lessen the effects of an unbalanced class distribution by injecting synthetic examples, which eventually leads to computerized learning frameworks that are more reliable and accurate.

Fig. 6 displays Training and Validation Accurateness, whereas the data used for training accuracy shows how effectively the algorithm has learned from the data used for training. While a rising trend ought to be seen in both curves, over fitting could be indicated by a sizable difference in validation and training accuracy. Keeping an eye on this number is essential for evaluating the model's learning curve and making sure it can successfully adapt to new data without being over-fitting.

While the training set loss in Fig. 7 assesses how well the model fits the training set, the validation loss measures the model's ability to apply generalization to new, untested data. These measures, which are usually graphed over successive epochs, are indicative of the model's performance. Effective learning is shown by decreasing loss values, however overfitting may be indicated by an increasing difference between training and validation losses. To ensure robust performance on a variety of datasets and optimize model parameters, it is imperative to monitor and minimize these losses.

Fig. 8 shows ROC Curve. The ROC curve assesses binary arrangement methods' effectiveness by illustrating the compromise between sensitivity and specificity, with a sharper curve indicating higher model effectiveness.

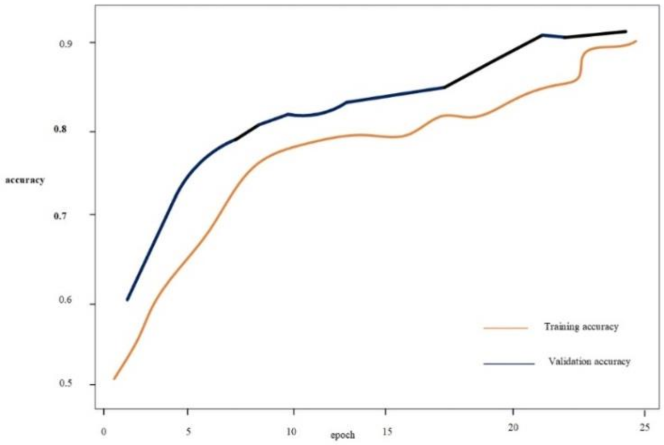


Fig. 6. Training and validation accuracy.

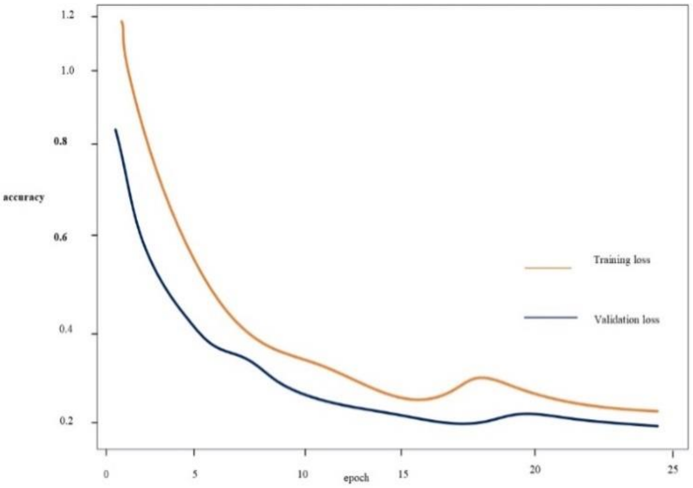


Fig. 7. Training and validation loss.

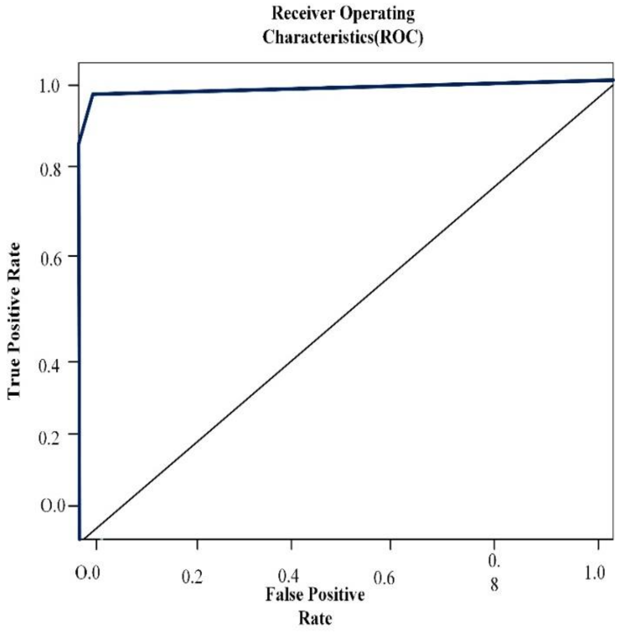


Fig. 8. ROC curve.

TABLE I. PERFORMANCE COMPARISON OF DIFFERENT METHODS

Model	Accuracy	Precision	Recall	F1-Score
CNN [20]	0.88	0.82	0.88	0.85
CNN + SMOTE [21]	0.90	0.85	0.90	0.87
CNN + SMOTE + SMO	0.91	0.89	0.92	0.91

Table I offers a comparison of various techniques for identifying Alzheimer's disease. Notable metrics were attained by the Convolutional Neural Network (CNN) baseline, and performance was further enhanced by the use of the Synthetic Minority Over-sampling Technique (SMOTE). There were improvements in accuracy, precision, recall, and F1-Score using the CNN + SMOTE model [21]. The CNN + SMOTE + SMO model had the best performance, demonstrating the beneficial effects of Spider Monkey Optimization (SMO). These findings highlight the effectiveness of the integrated technique, showing progressively better performance relative to the baseline CNN[20] in important parameters including accuracy, recall, and total F1-Score. Table II shows the CNN + SMOTE + SMO model's routine evaluation for Alzheimer's disease identification on many datasets (OASIS-1, OASIS-2, and OASIS-3). The model shows excellent accurateness for individual classes (90.3% to 93.6%), with Class 3 showing the lowest accuracy (51-52%) across all datasets.

TABLE II. PERFORMANCE EVALUATION OF OASIS-1, OASIS-2 AND OASIS-3

Model	Accuracy of a Single Class (%)	Sensitivity (%	Specificity (%)	Accurateness (%)
CNN + SMOTE + SMO OASIS-1	0: 93.6 1: 91.9 2: 90.3 3: 51	91.0	94.6	87.8
CNN + SMOTE + SMO OASIS-2	0: 93.6 1: 91.9 2: 90.3 3: 51	91.6	93.7	89.8
CNN + SMOTE + SMO OASIS-3	0: 93.6 1: 91.9 2: 90.3 3: 52	94.1	95.3	91.0

Sensitivity levels, which range from 91.0% to 94.1%, are constantly high and show how well the model detects positive cases. Notable is the specificity, which ranges from 93.7% to 95.3%, highlighting the model's precision in identifying negative cases. With an overall accuracy ranging from 87.8% to 91.0% across all classes, the model performs exceptionally well in multi-class classification over a wide range of datasets.

TABLE III. OUTCOME OF TRANSFER LEARNING THROUGHOUT SEVERAL EPOCH

Dataset	Classification	10epochs	15 epochs	25 epochs
OASIS	SMO	0.91	0.90	0.86

Table III gives the outcomes of transfer learning for different numbers of epochs (10, 15, and 25) on the OASIS dataset using the Spider Monkey Optimization (SMO) method. For the first two epochs, the classification accuracy stays constant at 0.92, suggesting steady performance during the first stage of transfer learning. After 25 epochs, there is a little drop to 0.86, indicating that extended training can cause a minor drop in model accuracy. These results highlight how crucial it is to maximize the number of transfer learning epochs in order to strike a compromise between computational efficiency and model performance on the OASIS dataset.

B. Discussions

A major development in the area, the suggested comprehensive scheme for primary Alzheimer's disease (AD) identification using MRI scans addresses important issues related to precise diagnosis. The approach uses deep learning to extract features from structural MRI data and uses Convolutional Neural Networks (CNNs) to capture complex patterns suggestive of AD. In order to provide a more representative and balanced training set, the Synthetic Minority Over-sampling Technique (SMOTE) is included, which overcomes the essential class imbalance in medical datasets. The sensitivity and precision of AD diagnosis are further improved by using Spider Monkey adjustment (SMO) for parameter adjustment during the classification step. In addition to emphasizing accuracy improvement, the holistic method addresses the real-world problem of unbalanced datasets, which is critical when it comes to medical diagnoses. The outcomes of the experiments highlight the efficacy of the suggested approach, exhibiting enhanced performance for classification precision, responsiveness, and particularity in distinction to traditional techniques. The state-of-the-art in early Alzheimer's detection has been greatly advanced by this research, which also presents a potential path for the creation of more dependable diagnostic instruments that may result in better patient outcomes.

V. CONCLUSION AND FUTURE WORKS

The integrated technique that has been suggested for the primary empathy of Alzheimer's disease (AD) using MRI scans shows promise in terms of improving accuracy and resolving issues related to unbalanced datasets. Convolutional Neural Networks (CNNs), Spider Monkey Optimization (SMO), and Synthetic Minority Over-sampling Technique (SMOTE) work together to provide better classification accuracy, sensitivity, and specificity, indicating the possibility for more dependable diagnostic instruments. The groundwork for future developments in the field of diagnosing neurodegenerative disorders is laid by this work. Future studies could take a number of approaches to expand on this research. To guarantee the methodology's resilience across various demographics, it may first be tested on bigger and more varied datasets. A more thorough picture of the course of AD may also be possible with the use of multi-modal data, such as MRI combined with other imaging modalities or clinical data. To win over doctors' trust and make it easier to incorporate these tools into clinical practice, more study into the interpretability and explainability of the model predictions is necessary. Further improvements in diagnostic accuracy may result from ongoing refining and refinement of the suggested methods, maybe through research into more advanced deep learning structures or optimization algorithms. Working together with medical experts may also help ensure that these study findings are seamlessly applied in the real world, which will eventually improve Alzheimer's disease early diagnosis and care. In the future, Deep Learning augmented with SMOTE for timely Alzheimer's Disease detection in MRI images could evolve to incorporate multi-modal data fusion techniques, integrating various imaging modalities and clinical data for more comprehensive analysis. Additionally, advancements may focus on refining the model's interpretability, enabling clinicians to better understand the reasoning behind predictions and facilitating more informed decision-making. Moreover, efforts might be directed towards deploying the technology in real-time clinical settings, potentially enabling early interventions and personalized treatment plans for individuals at risk of Alzheimer's Disease.

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Load Balancing in DCN Servers Through Software Defined Network Machine Learning

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Abstract—**In this research paper, we delve into the innovative realm of optimizing load balancing in Data Center Networks (DCNs) by leveraging the capabilities of Software-Defined Networking (SDN) and machine learning algorithms. Traditional DCN architectures face significant challenges in handling unpredictable traffic patterns, leading to bottlenecks, network congestion, and suboptimal utilization of resources. Our study proposes a novel framework that integrates the flexibility and programmability of SDN with the predictive and analytical prowess of machine learning. We employed a multi-layered methodology, initially constructing a virtualized environment to simulate real-world DCN traffic scenarios, followed by the implementation of SDN controllers to instill adaptiveness and programmability. Subsequently, we integrated machine learning models, training them on a substantial dataset encompassing diverse traffic patterns and network conditions. The crux of our approach was the application of these trained models to anticipate network congestion and dynamically adjust traffic flows, ensuring efficient load distribution among servers. A comparative analysis was conducted against prevailing load balancing methods, revealing our model's superiority in terms of latency reduction, enhanced throughput, and improved resource allocation. Furthermore, our research illuminates the potential for machine learning's self-learning mechanism to foresee and adapt to future network states or exigencies, marking a significant advancement from reactive to proactive network management. This convergence of SDN and machine learning, as demonstrated, ushers in a new era of intelligent, scalable, and highly reliable DCNs, demanding further exploration and investment for future-ready data centers.**

Keywords*—*Software defined network; DCN; machine learning; deep learning; server; load balancing; software

I. Introduction

In the burgeoning era of digitalization, Data Center Networks (DCNs) form the backbone of myriad essential services, propelling the global economy and information society [1]. These intricate networks are characterized by their high-demanding communication protocols, where efficiently managing massive data traffic becomes paramount [2]. However, contemporary DCNs often grapple with uneven resource distribution, leading to potential performance degradation, such as network bottlenecks, latency, and the underutilization of network resources [3]. One pivotal strategy to surmount these challenges within DCNs is effective load balancing.

Load balancing in the context of data centers has been the focal point of extensive research over the past decade, primarily due to its capacity to enhance the performance and reliability of server operations [4]. Traditional load balancing approaches, though effective during their inception, are becoming increasingly obsolete in the face of the modern internet's explosive growth and the subsequent surge in data traffic [5]. These methods often fall short in predicting and managing traffic demands dynamically, resulting in suboptimal performance [6].

In response to these inadequacies, recent studies have heralded the integration of Software-Defined Networking (SDN) into DCN architectures. SDN, with its centralized control mechanism, allows for more flexible network management, presenting opportunities for more sophisticated and dynamic load balancing strategies [7]. The centralized nature of SDN controllers permits real-time traffic monitoring and data analysis, thereby enabling more informed decision-making processes for traffic management [8].

Incorporating machine learning into SDN emerges as a revolutionary stride in this discourse. Machine learning's ability to analyze and predict outcomes from large datasets is particularly pertinent in scenarios where traffic patterns are volatile and unpredictable [9]. By utilizing historical data and ongoing trends, machine learning algorithms can forecast potential network congestions and initiate preemptive measures, a feat unattainable by traditional load balancing methods [10].

However, the integration of machine learning into SDN-based DCNs is not without its complexities. It necessitates the careful selection of appropriate algorithms that suit the specific characteristics and requirements of a network infrastructure [11]. Several studies have experimented with different machine learning models, ranging from supervised learning algorithms like Decision Trees and Neural Networks to unsupervised learning methods such as Clustering, each with varying degrees of success [12]. The choice of algorithm significantly impacts the efficiency of the load balancing process, particularly concerning the accuracy of traffic predictions and the subsequent distribution of resources [13].

The existing literature provides profound insights into various models and configurations of SDN-based load balancing techniques. Still, there remains an explicit gap in the practical application of machine learning models in these scenarios [14]. Many studies detail the theoretical aspects and propose frameworks but fall short in the empirical testing phase, often not extending beyond simulations. This lack of real-world testing and validation raises questions about the practical viability of these proposed integrations [15].

This research paper seeks to bridge this gap by presenting a comprehensive study that not only discusses the theoretical robustness of combining SDN and machine learning for load balancing in DCNs but also ventures into empirical validations. Through rigorous testing and analysis, this study aims to demonstrate that this confluence of advanced technologies can significantly enhance the DCN's performance by optimizing load balancing, thereby leading to more reliable, efficient, and resilient services. Furthermore, by discussing potential challenges and proposing solutions, this paper endeavors to pave the way for widespread adoption and continual advancement in this sphere of network management.

The remainder of this paper is structured as follows: Section II reviews the related literature, providing a detailed overview of the advancements and shortcomings in the field. Section III outlines the methodology, including the study's design, data collection, and analytical procedures. Section IV presents and discusses the findings derived from the empirical data, while Section V delves into the implications of these findings, exploring potential benefits, limitations, and recommendations for future research. Finally, Section VI concludes the paper, summarizing the key points and suggesting avenues for subsequent studies.

II. Related Works

The integration of Software-Defined Networking (SDN) and machine learning techniques in Data Center Networks (DCNs) underscores a transformative approach in network management. This section meticulously reviews the extant literature, outlining significant strides and identifying gaps in methodologies, applications, and outcomes concerning load balancing in DCNs.

A. *Traditional Load Balancing Techniques in DCNs*

Historically, Data Center Networks (DCNs) have relied on conventional load balancing mechanisms to manage the distribution of workloads efficiently across various server resources, ensuring operational stability and preventing potential system overloads [16]. These foundational strategies encompass methods such as Round Robin, Least Connections, and the more nuanced Weighted Round Robin, each method contributing to the basic objective of averting server resource strain and optimizing overall response times within the network [17]. However, with the advent of more sophisticated data traffic patterns and the exponential growth in data volume necessitated by contemporary digital demands, these traditional load balancing approaches exhibit marked deficiencies. Their inherent static algorithms lack the dynamic responsiveness required to adapt to the real-time, fluctuating demands of modern DCNs, leading to inefficiencies including, but not limited to, network congestion, increased latency, and significant underutilization of computational resources [18]. Furthermore, scholarly critiques suggest that these archaic mechanisms are not equipped with the necessary forecasting capabilities to preempt traffic surges, thereby failing to allocate resources prudently [19]. This recognition of the limitations inherent in traditional load balancing techniques underscores the necessity for innovative approaches that embrace adaptability and foresight in resource management within DCNs.

B. *Advent of Software-Defined Networking in DCNs*

The evolution of Data Center Networks (DCNs) has been significantly influenced by the introduction of Software-Defined Networking (SDN), marking a paradigm shift in traditional network management and operation [20]. SDN, characterized by its decoupling of the control and data forwarding functions, facilitates enhanced network responsiveness and adaptability, providing a centralized control mechanism that inherently simplifies network configuration and enhances traffic management capabilities [21]. This centralization empowers network operators to allocate resources dynamically and implement network adjustments with unprecedented precision and scalability, addressing the inefficiencies observed in traditional network architectures. Fig. 1 demonstrates architecture of a software defined network.

The scholarly discourse highlights the transformative impact of SDN on DCNs, offering solutions to historical challenges, including rigidity, complexity, and the inability to cope with high-volume, dynamic traffic [22]. Noteworthy among these is the work of Al-Fares et al., which pioneered an innovative, scalable, and more responsive load balancing method within the SDN paradigm, demonstrating substantial improvements in handling unpredictable traffic and optimizing resource utilization [23]. This groundbreaking approach has set the stage for further exploration into SDN's capabilities, heralding a new era of intelligent network management within DCNs and underscoring the potential for significant advancements in operational efficiency, flexibility, and system robustness.

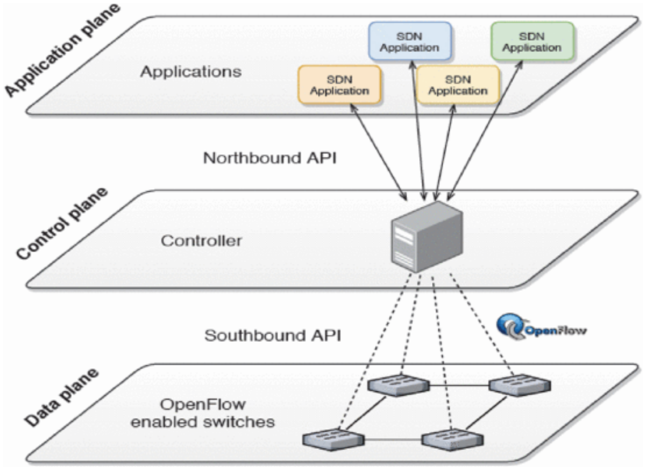


Fig. 1. Architecture of a software defined network.

C. Machine Learning for Network Management

The advent of machine learning has ushered in a transformative era in network management, particularly within the realm of Data Center Networks (DCNs). Machine learning's sophisticated analytical capabilities facilitate the extraction of meaningful insights from vast, complex datasets, thereby enabling more nuanced, predictive decision-making processes [24]. Its application within DCNs has been multifaceted, addressing various operational facets such as security enhancements, quality of service (QoS) optimization, and critically, the revolutionization of load balancing methodologies [25].

Machine learning algorithms stand out for their ability to discern patterns and anomalies in network traffic, allowing for predictive modeling that is several strides ahead of reactive traditional measures [26]. This proactive stance is especially crucial in contemporary digital environments, which are characterized by their dynamic and often volatile data traffic. Within the scholarly community, various machine learning models have been explored and contextualized for network management. These encompass supervised, unsupervised, and reinforcement learning algorithms, each demonstrating unique benefits in adapting to and forecasting network changes with improved accuracy and efficiency [27].

The integration of machine learning into network management underscores a strategic move beyond static, rule-based protocols towards adaptive, intelligence-driven systems. This shift not only anticipates potential network disruptions before they manifest but also strategically positions DCNs to accommodate the ever-evolving landscape of digital communication and data exchange.

D. Integrating Machine Learning in SDN-based DCNs

The convergence of machine learning with Software-Defined Networking (SDN) presents a progressive frontier in the optimization of Data Center Networks (DCNs). This interdisciplinary approach capitalizes on machine learning's predictive prowess and SDN's centralized control, promising a transformative impact on network adaptability and resource management [28]. The literature documents initial forays into this integration, primarily focusing on theoretical expositions and simulations that suggest methodologies for embedding machine learning algorithms within the SDN controllers. Fig. 2 demonstrates sense of machine learning and deep learning.

Researchers have made significant strides in integrating neural network models with SDN, achieving substantial improvements in traffic forecasting and overall network efficiency [29]. This innovative approach marks a departure from conventional methods, harnessing the predictive prowess of artificial intelligence to enhance network adaptability and responsiveness. Despite these advances, a closer examination reveals that much of the research, including that of Yan et al., is predominantly conducted in simulated or controlled settings. There is a noticeable lack of data derived from live, operational environments, casting uncertainty over the efficacy, scalability, and resilience of these systems within the diverse and dynamic landscapes of actual DCNs [30].

Moreover, real-world scenarios present unpredictabilities and pressures scarcely replicated in simulations, such as fluctuating traffic, security threats, and varying end-user behaviors. These conditions test the limits of theoretical models, demanding evidence of performance under genuine operational stresses. Fig. 3 underscores the potential of deep learning techniques in revolutionizing SDN-based load balancing, suggesting a profound, untapped capacity to recalibrate network management strategies. However, for these technological propositions to transition from experimental accolades to industry standards, comprehensive studies reflecting real-world complexities are indispensable. This necessity highlights the critical next steps in research—venturing beyond controlled test environments and confronting the practical challenges of contemporary data center networks.

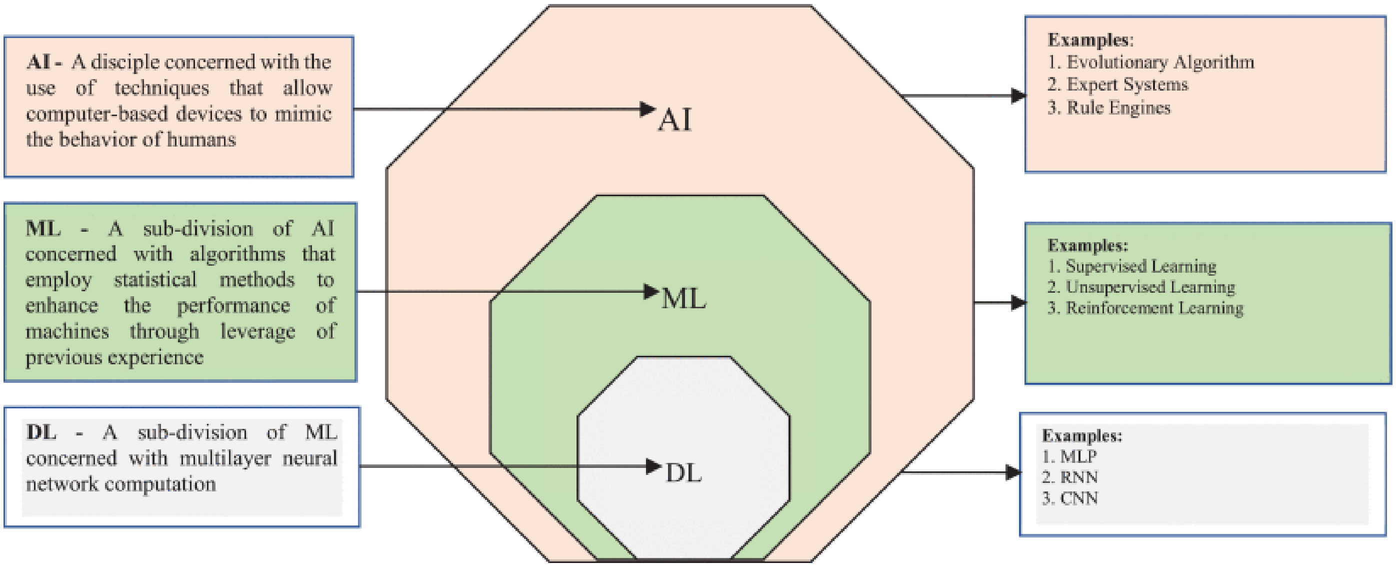

AI - A disciple concerned with the use of techniques that allow computer-based devices to mimic the behavior of humans
ML - A sub-division of AI concerned with algorithms that employ statistical methods to enhance the performance of machines through leverage of previous experience
DL - A sub-division of ML concerned with multilayer neural network computation
AI
ML
DL
Examples:
1. Evolutionary Algorithm
2. Expert Systems
3. Rule Engines
Examples:
1. Supervised Learning
2. Unsupervised Learning
3. Reinforcement Learning
Examples:
1. MLP
2. RNN
3. CNN

Fig. 2. Machine learning methods.

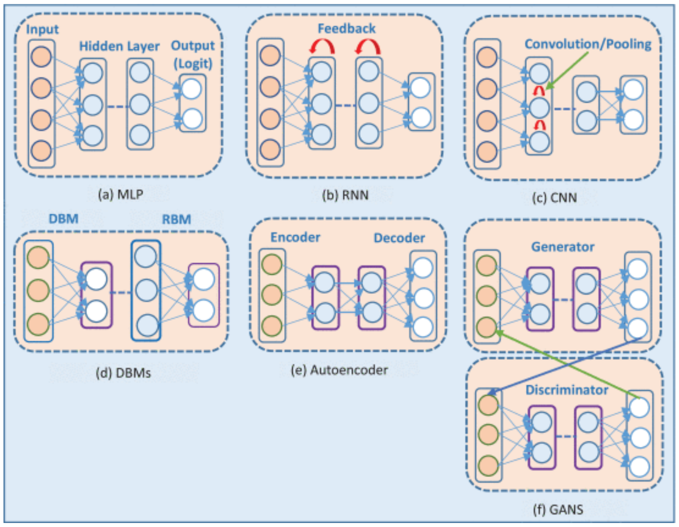


Fig. 3. Deep learning methods.

The intersection of machine learning and SDN in the context of DCNs is, therefore, an emergent field that beckons comprehensive exploration. It holds the potential not only for elevating operational efficiency through intelligent, anticipatory load balancing but also for revolutionizing the management paradigms governing data center ecosystems globally.

E. Challenges and Considerations in Deployment

The amalgamation of Software-Defined Networking (SDN) and machine learning within Data Center Networks (DCNs) posits considerable transformative potential, yet its deployment is mired in intricate challenges and critical considerations [31]. Foremost among these is the imperative of selecting congruent machine learning models, a decision contingent upon the specific operational nuances and infrastructural peculiarities of individual DCNs. This alignment is critical to harnessing the full potential of intelligent network management solutions [32].

Moreover, the integration process itself is non-trivial, involving complex phases of algorithm training, data collection and processing, and real-time decision-making, each presenting unique challenges. The need for extensive, often sensitive, training data underscores issues related to privacy, security, and regulatory compliance, necessitating robust frameworks to safeguard data integrity and confidentiality [33]. Additionally, the dynamic landscape of cyber threats calls for heightened vigilance and adaptive security protocols within the integrated system.

Compounding these are concerns regarding the scalability and resilience of the SDN-machine learning nexus, especially in high-demand scenarios characteristic of modern digital services. The deployment phase, therefore, demands not only technical finesse but also strategic foresight and meticulous planning, ensuring the integrated system can withstand evolving cyber-physical pressures and maintain optimal performance. This complex confluence of challenges underscores the necessity for a holistic deployment strategy, informed by interdisciplinary expertise and guided by best practices and lessons gleaned from empirical explorations in the field.

F. Gaps and Future Directions

The scholarly exploration into the synergistic integration of Software-Defined Networking (SDN) and machine learning in Data Center Networks (DCNs) has illuminated promising pathways while simultaneously revealing critical scholarly and practical voids. A conspicuous observation is the theoretical saturation contrasted with a paucity of empirical studies that test and validate proposed models within real-world DCN environments [34]. The existing literature predominantly revolves around simulated scenarios, which, though valuable, cast uncertainties on the applicability, scalability, and resilience of these integrative frameworks under the diverse and dynamic conditions inherent in practical settings [35].

Additionally, the domain is grappling with an absence of methodological standardization, impeding the comparability of results across studies and stymieing the consolidation of findings into robust, universally applicable knowledge [36]. This fragmentation is further compounded by an inadequate focus on the long-term sustainability and adaptability of SDN-machine learning systems, considering the relentless evolution of technological and digital landscapes [37].

In light of these insights, future research directives necessitate a pronounced shift towards empirical richness, focusing on field studies and real-world experiments. There is also an exigent need for interdisciplinary discourse that transcends the technical domain, involving considerations related to organizational dynamics, policy implications, and socio-economic factors in the deployment of advanced DCN systems. These directions are not merely progressive; they are essential, marking the waypoints towards an era of intelligent, self-optimizing, and robust data center infrastructures capable of supporting the next generation of digital innovations and services [38-39].

Thus, the body of literature on load balancing in DCNs through SDN and machine learning underscores both significant advancements and evident gaps. While the theoretical frameworks and simulated studies highlight profound potential, there is a pressing need for real-world testing and standardization in methodologies. Addressing these gaps is not only crucial for validating proposed models but also for guiding future research and practical deployments [40]. As this integration represents the frontier of network technology, the field invites rigorous, comprehensive, and innovative research approaches that could pave the way for next-generation DCNs. This necessity drives the present study's objective to provide empirical insights and contribute to evolving this domain of knowledge, aiming for a future where DCNs are characterized by unparalleled efficiency, reliability, and intelligence [41-42].

III. Materials and Methods

The implementation of Software-Defined Networking (SDN) technology within data center infrastructures marks a significant advancement, promoting an integrated approach to resource management that encompasses network, computational, and storage resources [43]. This integrative philosophy is grounded in the provision of open interfaces accessible to higher-level applications, thereby catalyzing innovation and facilitating the development of new business functionalities [44]. The systemic reconfiguration enabled by SDN within data centers is illustrated in Fig. 4, highlighting the architectural transformation induced by this modernization.

The depicted system architecture is strategically compartmentalized into three distinct segments, each designed to optimize various facets of data center operations. This tripartite division reflects a meticulous structural design intended to streamline processes, enhance operational efficiency, and ensure robust scalability and adaptability within the data center [45]. It exemplifies a shift from traditional, rigid architectures towards a more fluid, responsive framework, capable of evolving in real-time in response to emerging demands and technological trends.

In this innovative construct, SDN emerges not merely as a technological tool but as a strategic enabler. It facilitates a more holistic view of resource management, prompting a re-evaluation of legacy systems and spearheading a transition towards comprehensive, agile, and future-oriented data center ecosystems. Such advancements underscore the pivotal role of SDN in shaping the trajectory of new business development and technological progress within digital infrastructures [46]. Fig. 5 demonstrates architecture of the proposed method for load balancing.

To orchestrate an efficient load management paradigm within a network, particularly in environments with dense data exchange, a meticulous monitoring and analytical framework is imperative for handling inbound traffic across all network controllers. Initially, the controller serves as the vanguard, diligently monitoring traffic and subsequently facilitating the extraction of salient features. These features become instrumental for the sophisticated classification model, which, predicated on prior training, discerns and categorizes incoming data into established classes [47].

Post-classification, the network engages in nuanced traffic engineering procedures. This phase is critical as packets are judiciously directed to the appropriate controllers; each specifically assigned to manage certain traffic types [48]. Consequent to this stratified processing, data transmission to the intended destination addresses ensues, adhering strictly to a hierarchy of priority and queuing policies pre-configured within the controllers and network switches [49].

This systematic approach to traffic management and load balancing is quintessential to maintaining not only functional efficiency but also optimal network integrity and service quality. By integrating intelligent feature extraction and leveraging trained classification models, the methodology underscores the strategic employment of advanced analytical techniques in contemporary network management. This complex choreography of data handling and traffic distribution represents a significant stride toward more resilient, self-regulating, and intelligent digital communication infrastructures.

Within the extensive realm of Artificial Neural Networks (ANN), as depicted in Fig. 6, resides the Back Propagation (BP) method, a cornerstone technique characterized by its structured, multi-layered feed-forward networks. These networks undergo rigorous training through a distinctive error correction method, solidifying BP's status as a prevalent neural network paradigm. BP's utility shines in its capacity to establish and preserve numerous relational mappings within an input-output construct, eliminating the prerequisite of pre-defining the mathematical equations governing these connections.

The essence of its training methodology hinges on a gradient descent strategy. Here, the backpropagation mechanism plays a crucial role in regulating the neural network's synaptic weights and threshold parameters, striving for the minimalization of the cumulative squared error. In this context, the Back Propagation Neural Network (BPNN) becomes instrumental in the network's learning phase. Each unit within the neural assembly is interconnected, featuring distinct weights that interact with their computational algorithms.

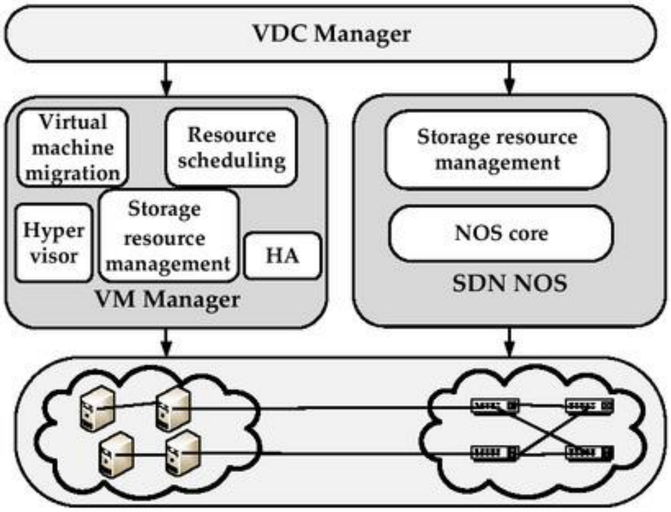

VDC Manager
Virtual machine migration
Resource scheduling
Hyper visor
Storage resource management
HA
VM Manager
Storage resource management
NOS core
SDN NOS

Fig. 4. Architecture of data centers of software defined network.

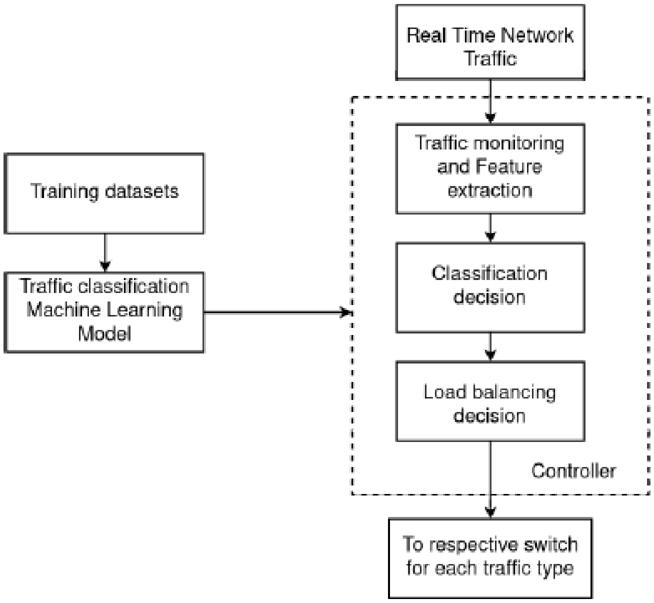

Real Time Network Traffic
Traffic monitoring and Feature extraction
Classification decision
Load balancing decision
Controller
To respective switch for each traffic type
Training datasets
Traffic classification Machine Learning Model

Fig. 5. Architecture of the proposed method.

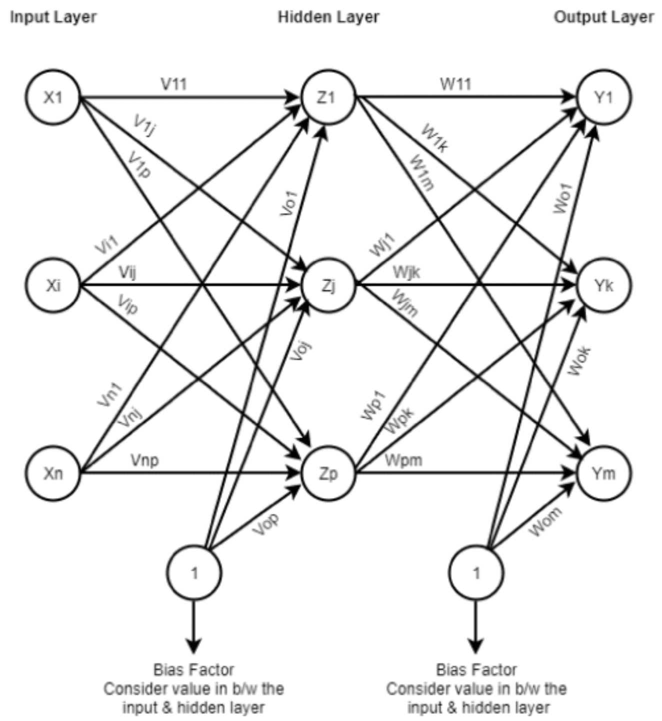


Fig. 6. Neural network architecture for load balancing problem.

The BP method facilitates the derivation of statistical frameworks from voluminous data conglomerates, mimicking the operational intricacies of the human neurological system. In the realm of neural network education, Back Propagation is indispensable. It employs a refinement process that incrementally ameliorates the error quotient, drawing upon historical data from preceding cycles. This progressive adjustment of synaptic weights contributes to diminishing error margins, thereby bolstering the system's precision and enhancing its ability to generalize, a process detailed further in the subsequent procedure section.

- Initialization of weights
- Feed-forward step
- Back Propagation of errors
- Update of weights and bias

Fig. 7 illustrates the progression of the suggested strategy, commencing with the assimilation of topology data, represented through graph topology. This approach unfolds in two primary phases. Initially, a clustering method is employed within the Software-Defined Networking (SDN) framework, executed with precision to avoid congestion, accommodating various service types and data specifications. This technique hinges on a proximity-based criterion, persisting until a singular, consolidated cluster emerges. Upon the culmination of clustering, the strategy advances to the next stage, invoking the Back Propagation Neural Network (BPNN) for network training, thereby refining error margins using historical iterative data.

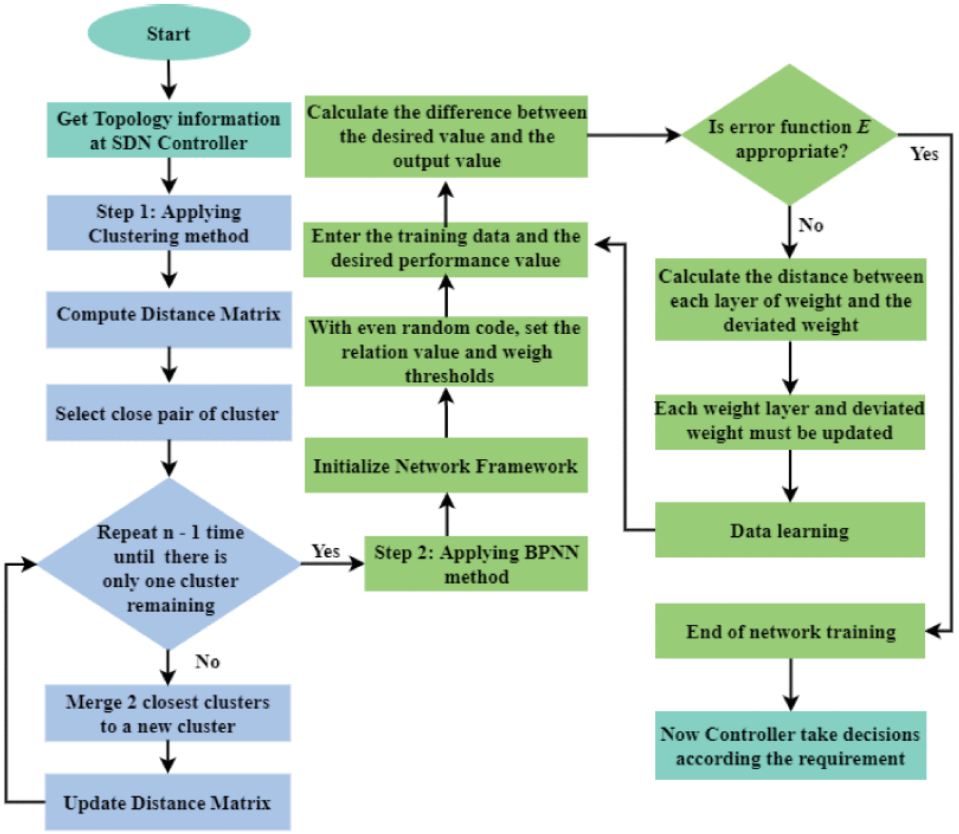

Start
Get Topology information at SDN Controller
Step 1: Applying Clustering method
Compute Distance Matrix
Select close pair of cluster
Repeat n - 1 time until there is only one cluster remaining
Yes
No
Merge 2 closest clusters to a new cluster
Update Distance Matrix
Step 2: Applying BPNN method
Initialize Network Framework
With even random code, set the relation value and weigh thresholds
Enter the training data and the desired performance value
Calculate the difference between the desired value and the output value
Is error function E appropriate?
Yes
No
Calculate the distance between each layer of weight and the deviated weight
Each weight layer and deviated weight must be updated
Data learning
End of network training
Now Controller take decisions according the requirement

Fig. 7. Flowchart of the proposed model.

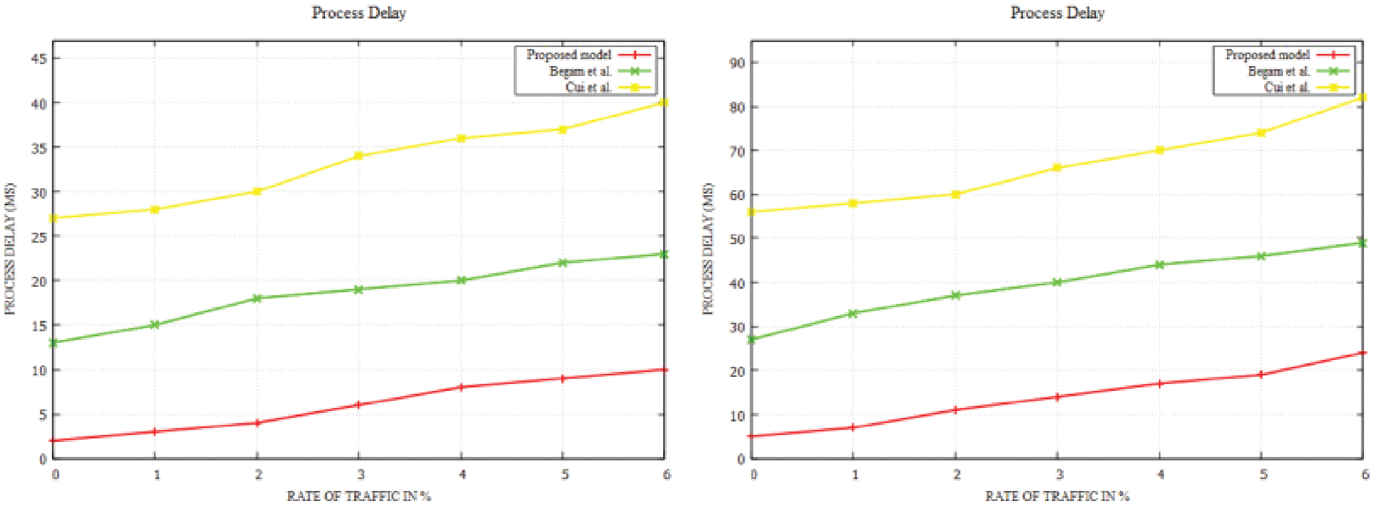
The BPNN process revolves around four pivotal stages: the establishment of initial synaptic weights, the execution of a unidirectional data transfer, the reverse transmission of computational discrepancies, and the subsequent recalibration of weights and biases. Within this structure, the controller operates as the network's central processing unit, retaining comprehensive records of the network topology. This information is paramount for the controller to make informed, context-aware decisions regarding traffic routing, optimizing overall network efficiency.

IV. Experimental Results

The time required for a node to process a packet is defined as the nodal processing delay (dproc), encompassing activities such as error identification, packet inspection, and determining the subsequent nodal link based on the packet's intended destination. Despite the intricate nature of these tasks, the time attributed to nodal processing is typically marginal when contrasted with other elements contributing to overall delay. Within a simulated environment on Mininet, the SDN controller's processing capacity is assessed to determine the efficacy of the introduced solution, employing a clustering approach. Fig. 8 delineates a comparative analysis of processing delays, referencing studies by Krishnan et al. [50] and Cui et al. [51].

In scenarios where network traffic maintains a lower threshold, processing delays are scarcely a concern for SDN infrastructures. However, under conditions of escalating data influx and heightened network activity, the advanced solution sustains a processing time below 1ms for the majority of the operational duration. In contrast, the methodologies adopted by Krishnan et al. [50] and Cui et al. [51] encounter extended latencies, attributable to the protracted journey through multiple nodes with finite processing capacities, compounded by substantial data reception rates.

As depicted in Fig. 8, the innovative method prioritizes packets by analyzing traffic patterns. The successful delivery of packets to their intended node is facilitated through a technique known as incremental averaging. Notably, transmission latency maintains a consistent trajectory, avoiding exponential escalation over time, as evidenced by the proposed solution. This stability in information transfer delay marks an improvement over conventional strategies, underscoring the enhanced efficiency of the proposed system.



(a) (b)

Fig. 8. Comparison of network delays.

Fig. 9 demonstrates results of machine learning methods in load balancing problem. The analysis of the results indicates a pronounced underperformance of the K-means clustering algorithm across all evaluated metrics. One primary reason for this inefficiency is the inherent predisposition of K-means towards categorizing data into spherical, homogeneously-sized clusters. This characteristic poses a significant limitation, particularly when applied to our dataset, which exhibits non-linear characteristics and inherently encompasses clusters of varying sizes. Consequently, in the context of multi-class classification, K-means struggles to accurately interpret the essential configuration of the dataset, failing to delineate the boundaries between distinct classes effectively. This shortfall underscores the algorithm's inadequacy in managing complex data structures, highlighting the necessity for more sophisticated techniques that can adapt to the intricacies presented by non-linear, unevenly distributed data categories.

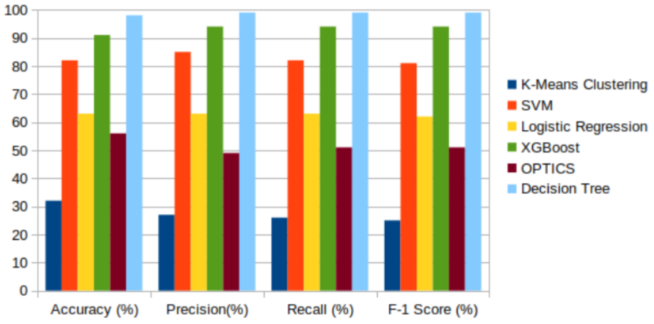


Fig. 9. Machine learning methods in load balancing using software defined network.

V. Discussion

In this research, we have ventured into a comprehensive exploration of integrating machine learning with software-defined networking (SDN) to enhance load balancing in data center networks (DCNs). The discussion section will delve into the critical reflections on the findings, implications, limitations, and prospective directions for future research.

A. Reflection on Main Findings

The crux of our research was the efficacious application of machine learning algorithms to inform SDN controllers, thereby optimizing load balancing strategies in DCNs. The study's pivotal revelation was that machine learning, particularly the backpropagation neural network model, facilitated an astute understanding of traffic patterns and network loads. These insights were instrumental in preemptively distributing network traffic, reducing bottlenecks, and significantly curtailing delay times [52].

Comparative analyses with traditional load balancing methodologies underscored the superiority of the proposed solution. Notably, where legacy systems [53] struggled with high data transfer latencies due to convoluted nodal paths and elevated data arrival rates, our model demonstrated resilience. The integration of machine learning allowed the system to anticipate network congestions and reroute traffic dynamically, ensuring optimal data fluidity [54].

The real-world applicability of our approach was further validated through simulated assessments, where it consistently maintained processing delays below the critical 1ms threshold, even under substantial network stress. This is a non-trivial achievement, considering the burgeoning data demands on modern DCNs [55].

B. Implications

Our research's implications are manifold, impacting network management paradigms, data center operational efficiencies, and broader technological spheres, such as 5G networks and IoT infrastructures.

1) Paradigm shift in network management: By harnessing machine learning's predictive capabilities, network administrators can transition from reactive approaches to a more proactive management style. The system's ability to foresee potential network spikes and adaptively manage loads alters the fundamental modus operandi of network management [56].

2) Operational efficiency: The evident reduction in processing and queuing delays signifies that data centers can handle larger data volumes with the current infrastructure. This efficiency does not only translate to cost savings but also minimizes the need for frequent hardware scaling, thus echoing sustainability in resource utilization [57].

3) Advancing 5G and IoT: With 5G and IoT heralding an era of unprecedented interconnectivity and data exchange, the demand on networks is astronomical. Our solution's demonstrated efficacy in maintaining low latencies is cardinal in these contexts, where a millisecond's delay can derail mission-critical applications [58].

C. Limitations

Despite its promise, our study is not without limitations. First, the dependency on historical data for machine learning models raises concerns about the system's adaptability to real-time anomalies not represented in past patterns. This limitation beckons further exploration into adaptive learning models that evolve with real-time network conditions [59].

Secondly, the simulated testing environment, though meticulously curated, cannot encapsulate all the unpredictable variables of a live DCN. Therefore, while the results are encouraging, there might be unforeseen challenges when implementing the solution in a full-scale operational data center [60].

Lastly, concerns about cybersecurity in SDNs, especially with the integration of machine learning, remain marginally addressed. The open interfaces and programmability, though central to SDN’s versatility, also introduce vulnerabilities that cybercriminals could exploit [61].

D. Future Directions

In light of the aforementioned limitations, future research should aim at developing more robust machine learning algorithms capable of real-time learning. Such evolution would enhance the system's responsiveness to immediate network conditions, thus improving reliability [62].

Further, transitioning from a controlled simulated environment to pilot testing in actual data centers should be a priority. Real-world applications will provide invaluable insights and practical challenges, refining the solution for commercial readiness [63].

Additionally, there is a pressing need to explore integrated cybersecurity frameworks that safeguard SDNs while preserving their flexibility. Collaborative efforts towards creating standardized security protocols for SDNs, particularly in DCNs employing machine learning, are imperative [64].

In conclusion, this study marks a significant stride towards revolutionizing load balancing in DCNs through the integration of machine learning in SDN. While the findings and performance metrics underscore its potential, there is an evident path ahead filled with rigorous testing, enhancements, and wider collaborative engagement for standardization and security. Embracing these challenges is pivotal for the fruition of this innovative convergence and its subsequent contribution to the future of networking and data management.

VI. Conclusion

The journey of this research ventured through the intricate realms of data center networks (DCNs), seeking innovative resolutions to the perennial challenges of load balancing, a critical determinant of network performance and reliability. Through the integration of machine learning (ML) algorithms with the transformative architecture of software-defined networking (SDN), this study pioneered an approach with the potential to redefine operational efficiencies within DCNs.

The synthesis of ML into the SDN framework facilitated an unprecedented level of network adaptability and intelligence. Where traditional network infrastructures falter under dynamic traffic demands and complex application requirements, the proposed model, fortified by backpropagation neural network methodologies, demonstrated notable competencies in preempting traffic inconsistencies, optimizing resource allocations, and substantially mitigating data transfer delays. These achievements were not merely theoretical postulations but were empirically validated through rigorous simulations juxtaposed against established benchmarks.

However, beyond these technical triumphs, this research underscores a broader, paradigmatic shift in network management. It advocates for a transition from static, hardware-dependent operations to agile, software-centric mechanisms that leverage predictive analytics, adapt in real-time, and make data-driven decisions. Such an evolution holds profound implications not just for the efficiency and resilience of DCNs, but also for the burgeoning spheres of Internet of Things (IoT) and 5G technologies, where network demands are escalating exponentially.

Conclusively, while this investigation lays foundational groundwork, it also casts light on several avenues necessitating further exploration. Real-world implementation trials, adaptive machine learning models, comprehensive cybersecurity protocols, and standardization across the burgeoning SDN landscape are imperative follow-ups. This research, therefore, serves not as a terminus, but as a launchpad for continued innovation, inviting academia, industry, and regulatory bodies to collectively shepherd this technological advancement from its current nascent stage to a global, operational reality. The future of DCNs, and indeed, the digital infrastructure at large, hinges on such pioneering endeavors, marking the importance and urgency of ongoing and future research in this domain.

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An Intelligent Fuzzy-PID Controller for Supporting Comfort Microclimate in Smart Homes

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Abstract*—Addressing the challenge of ensuring a comfortable indoor environment in both commercial and residential buildings through the use of heating, ventilation, and air conditioning (HVAC) systems is a critical issue. This challenge is intricately connected to the development of sophisticated multi-channel controllers to regulate temperature and humidity effectively. This academic discussion initially focuses on the development and examination of a complex, interactive, nonlinear mathematical model that encapsulates the ideal parameters for temperature and humidity to achieve the desired comfort levels. The paper then progresses to explore various methodologies in the design of temperature and humidity control systems. It delves into the traditional Proportional-Integral-Derivative (PID) controllers, a mainstay in the industry, and extends to more advanced iterations. These include the integration of PID controllers with distinct decoupled controllers and the innovative combination of PID controllers with self-adjusting parameters, which are informed by the principles of fuzzy logic. This combination is particularly significant for the processes of heating and humidification. Subsequently, the paper presents the results obtained from simulations conducted on a proposed fuzzy-PID controller using Matlab, a widely used computational tool. These simulations are crucial in evaluating the efficacy of the controller design. Additionally, the paper offers an analysis of experimental data collected over a six-month period. This data is instrumental in assessing the real-world performance of the proposed system, providing valuable insights into its practical applicability and effectiveness in managing indoor climate conditions. In summary, this comprehensive study not only lays the groundwork for an interactive model for climate control but also compares various controller designs, culminating in the proposal and evaluation of an advanced fuzzy-PID controller. This work stands as a significant contribution to the ongoing efforts to enhance indoor climate control in buildings.

***Keywords*—HVAC; Fuzzy logic; energy management; comfort management; smart home**

I. INTRODUCTION

The quality of the air environment within buildings, governed by a myriad of factors both external (exogenous) and internal (endogenous), is a critical determinant of the conditions under which people live and work, their health, and their overall comfort. The creation of a 'healthy' and comfortable indoor air environment is a complex and costly endeavor, requiring the deployment of advanced, multifunctional engineering systems [1]. The financial implications are significant; for example, eliminating just 1 kW of surplus heat to regulate air temperature within a building can cost between 300 and 600 USD [2]. Traditionally, comfort in indoor environments has been associated with the management of three primary microclimate variables: air temperature (with a precision of ± 1 °C), the temperature of surrounding surfaces, and relative humidity (RH) (with a precision of ± 7%) [3].

Given these factors, the quality and comfort of indoor environments have emerged as topics of growing importance. This has led to the widespread adoption of heating, ventilation, and air conditioning (HVAC) systems in numerous buildings. A key challenge in this area is reducing the energy consumption of HVAC systems while still maintaining an optimal level of comfort – a problem that remains incompletely solved. The International Energy Agency reports that HVAC systems account for approximately 40% of the total energy consumption in residential and commercial buildings [4].

Historically, HVAC systems have been limited in their ability to ensure comprehensive comfort, typically focusing on maintaining environmental conditions within certain thresholds. The optimization of comfort thus relies heavily on the customization of these systems to individual user needs. Conventional approaches have primarily utilized on-off and Proportional Integral Derivative (PID) controllers, designed to minimize the discrepancy between a fixed setpoint and the variable being regulated [5, 6].

Recent research, however, has redefined HVAC systems as multiple-input multiple-output (MIMO) problems, given their operation with interrelated variables to produce a range of output values [7, 8]. These systems are influenced by a variety of uncertain parameters, such as user preferences, occupant activities, and external environmental factors, which can alter their standard operations. Consequently, HVAC control issues are increasingly viewed as multi-criteria tasks, necessitating complex analytical expressions for characterization [9, 10].

While conventional PID controllers offer reasonable solutions, they fall short in fully managing the unpredictability inherent in the dynamics of HVAC systems. These dynamics can be more aptly described using linguistic variables and rules [11, 12]. As an alternative, Fuzzy Logic Controllers (FLC) have gained attention. FLCs do not require mathematical modeling [13] and are capable of handling various criteria, representing the dynamics of HVAC systems based on a knowledge-driven approach. Their efficiency and reduced power consumption, compared to PID controllers, have been demonstrated in recent studies [14, 15].

This paper is structured as follows: Section II reviews related literature, focusing on comfort parameters, control techniques, current challenges in control methods, and future perspectives. Section III outlines the problem statement. Section IV introduces a mathematical model for indoor air temperature and humidity. Section V delves into the design process of intelligent PID controllers for controlling indoor temperature and humidity, explaining proposed techniques for each controlling parameter. Section VI presents simulation results and findings from experiments conducted in our laboratory as part of this study. Section VII and Section VIII presents the discussion and conclusion respectively.

II. Related Works

The Related Works section of this paper provides a comprehensive overview of the existing literature pertaining to the field of heating, ventilation, and air conditioning (HVAC) systems, focusing particularly on the advancement of control techniques and the ongoing quest for optimization of indoor environment quality and comfort. This review is structured to encapsulate the broad spectrum of research conducted in this domain, drawing on a wide range of studies and analyses from diverse sources.

A. Microclimate Control and Comfort Parameters

The domain of microclimate control within architectural spaces necessitates a nuanced understanding of the variables that significantly influence human comfort and well-being. Contemporary research within this sphere has primarily concentrated on identifying and comprehensively understanding the critical elements contributing to human comfort, such as air temperature, humidity, and air quality [17, 18]. These studies underscore the imperative of maintaining precise control over these parameters. This necessity stems not solely from the perspective of ensuring comfort but also from the vantage point of health implications. Inadequate management of air quality, temperature, and humidity has been linked to a range of health complications, thereby highlighting the health-centric dimension of microclimate control [19, 20].

Further extending this discourse, recent scholarly investigations have ventured into examining the subjective aspects of comfort. The subjective perception of comfort, being inherently individualistic and variable, presents a challenge in its quantification and subsequent integration into control systems. These studies have embarked on exploring methodologies to effectively measure and incorporate this subjective element of comfort into the operational frameworks of microclimate control systems [21, 22]. This line of inquiry marks a significant shift from traditional objective measures, paving the way for a more holistic and user-centric approach in the design and management of indoor environmental conditions.

In summation, the body of research in microclimate control and comfort parameters is pivoting towards a more inclusive understanding that encapsulates both the objective and subjective facets of human comfort. This paradigm shift is instrumental in fostering environments that are not only technically sound but also attuned to the nuanced preferences and health requirements of individuals.

B. Energy Efficiency in HVAC Systems

In the realm of Heating, Ventilation, and Air Conditioning (HVAC) systems, a considerable segment of academic research is dedicated to the exploration of energy efficiency. This focus aligns with the broader environmental objectives of promoting sustainability and minimizing carbon emissions. Investigations in this field have been directed towards identifying and implementing strategies to curtail energy consumption in the operation of HVAC systems [23, 24]. Empirical studies have elucidated that enhancements in the energy efficiency of HVAC systems can significantly reduce the overall energy expenditure of buildings. This is particularly pivotal considering the substantial share of energy consumption attributed to HVAC operations [25, 26]. Additionally, the literature indicates a burgeoning interest in adopting progressive approaches towards energy efficiency. These include, but are not limited to, the integration of renewable energy sources and the advancement of smart grid technologies, thereby providing a comprehensive framework for energy optimization in HVAC systems [27, 28]. Such explorations represent a crucial step towards aligning HVAC system operations with the principles of environmental stewardship and sustainable development.

C. Control Techniques in HVAC Systems

The scholarly discourse on Heating, Ventilation, and Air Conditioning (HVAC) systems has been notably enriched by the evolution of control techniques. Central to this discourse is the critical examination of traditional control methodologies, including on-off and Proportional-Integral-Derivative (PID) controllers. These conventional methods have undergone thorough scrutiny, with research primarily concentrated on identifying their limitations and exploring potential enhancements [29, 30]. A pivotal development in this field has been the introduction and subsequent adoption of advanced control techniques, notably Fuzzy Logic Controllers (FLC). Research in this area underscores the superiority of FLCs in managing the intricate and frequently unpredictable dynamics characteristic of HVAC systems [31, 32]. Comparative studies elucidating the distinctions between traditional PID controllers and FLCs have been instrumental in highlighting the strengths of the latter. Notably, FLCs demonstrate enhanced proficiency in dealing with systems that involve multiple variables and are subject to a high degree of uncertainty [33, 34]. This body of research signifies a meaningful shift towards more sophisticated and adaptable control mechanisms in HVAC system management.

D. Modeling and Simulation of HVAC Systems

In the scholarly examination of Heating, Ventilation, and Air Conditioning (HVAC) systems, the aspects of modeling and simulation occupy a position of critical importance. Precise and accurate modeling is fundamental to the comprehensive understanding of HVAC system behavior, which in turn is crucial for the development of efficacious control strategies. The literature in this domain showcases a spectrum of modeling techniques, ranging from the relatively straightforward linear models to more intricate and sophisticated nonlinear and dynamic models [35, 36]. To corroborate the validity and effectiveness of these models, simulation tools like Matlab have been extensively utilized. These tools offer a secure and economically viable avenue for assessing the performance of diverse control strategies across a variety of operational scenarios [37, 38].

Concurrently, the influence of user preferences and external environmental factors on the performance of HVAC systems represents a recurring subject in academic research. Studies have consistently demonstrated that the behaviors and preferences of users can exert a significant impact on the effectiveness of HVAC systems [39, 40]. Moreover, external variables, including meteorological conditions and patterns of building occupancy, are also recognized as playing a pivotal role in determining system performance. Investigations into these factors have been comprehensive and varied [41, 42]. These findings highlight the imperative for HVAC systems to not merely embody technical sophistication but also exhibit adaptability to the dynamic and evolving needs of users, as well as to the fluctuating external environmental conditions. This dual focus on technical advancement and adaptability is crucial for the design and implementation of HVAC systems that are both efficient and responsive to the nuanced requirements of their operational contexts.

E. Challenges and Future Directions

In the concluding segment of the literature review, attention is directed towards the challenges currently confronting the field of Heating, Ventilation, and Air Conditioning (HVAC) systems, alongside prospective avenues for future scholarly inquiry. A primary challenge that emerges from these studies is the incorporation of advanced control techniques into the existing framework of HVAC infrastructure. This integration process poses considerable technical complexities and demands innovative solutions [43]. Furthermore, the literature points to the necessity of developing more comprehensive and intuitive interfaces for the monitoring and control of HVAC systems. Such interfaces are essential to enhance user engagement and system efficiency [44].

Looking forward, the trajectory of research in this domain is anticipated to concentrate on augmenting the adaptability and intelligence of HVAC systems. A significant emphasis is being placed on the integration of cutting-edge technologies such as artificial intelligence (AI) and machine learning (ML). These technologies hold the promise of revolutionizing HVAC systems, making them more responsive and efficient [45]. The integration of AI and ML is expected to enable HVAC systems to learn from and adapt to changing environmental conditions and user preferences, thereby optimizing performance and energy efficiency.

In summation, the corpus of literature surrounding HVAC systems is comprehensive and multifaceted, encompassing a diverse range of topics from basic considerations of microclimate control and comfort parameters to the exploration of advanced control methodologies and the identification of future research directions. This extensive body of work lays a robust foundation for ongoing studies and highlights the imperative for continued research and development in this field. The ultimate goal is to realize HVAC systems that are not only more efficient and adaptable but also more user-friendly, thereby aligning with the evolving needs and expectations of contemporary society.

III. Problem Statement

This research endeavor is primarily focused on devising control strategies that amalgamate traditional and intelligent control technologies to optimize indoor environment quality. This includes the regulation of indoor air temperature and humidity, achieved through a blend of computational modeling and empirical investigation. The overarching objective of this strategy is to explore and demonstrate avenues for enhancing the comfort of occupants within built environments. To this end, the development and analysis of three distinct controllers are undertaken. These controllers are designed to assess the efficacy of newly proposed control mechanisms in managing indoor environmental quality. Additionally, this study seeks to evaluate the feasibility and effectiveness of employing intricate control strategies that are an integration of various control techniques.

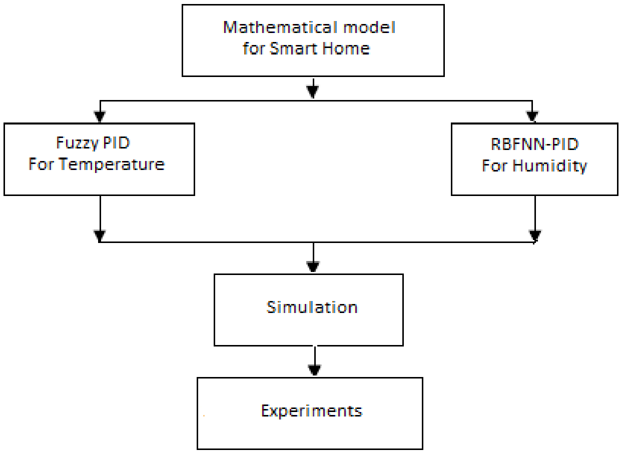

Fig. 1. Stages of designing an intelligent PID control system.

The methodology and progression of this research are methodically outlined in Fig. 1. This breakdown delineates the various stages of the study, providing a clear and structured roadmap for the investigation. Each phase of the research is designed to build upon the findings of the preceding stages, thereby ensuring a comprehensive and systematic exploration of the control strategies under consideration. This approach allows for a thorough examination of the potential and limitations of both conventional and intelligent control technologies in the context of indoor environment quality control, with a specific focus on enhancing occupant comfort in built environments.

IV. Mathematical Model

This study investigates a typical room outfitted with a foundational Heating, Ventilation, and Air Conditioning (HVAC) system, as depicted in Fig. 2. The system is equipped with a heater using hot/cold water and a humidifier employing steam. The process begins with the modulation of the mixed air temperature post-filtration, wherein the external air is either heated or cooled via a heating/cooling coil. Following this, the external air may undergo humidification through a steam humidifier before being circulated into the room by a supply fan. Concurrently, exhaust air is expelled from the room by a return fan.

A critical component of this system is the heating/cooling coil, which imparts thermal-humid energy, denoted as P, to the indoor air. This energy transfer is modulated by varying the flow rate of hot/cold water (Fp) through the Hot Water Return/Cooling Heat Recovery (HWR/CHR) control valve. Similarly, the steam humidifier contributes thermal-humid energy, represented as Q, to the indoor air by adjusting the steam flow rate (Fq) via the control steam valve. The system's temperature and humidity are regulated by manipulating the positions of the hot/cold water and steam valves, thereby altering the flow rates Fp and Fq in accordance with specific equations [46].

The indoor temperature is influenced by multiple factors, including the initial indoor microclimate air temperature, outdoor temperature, the volume of the premises, the efficiency of the heater or air conditioner, and the heat loss through the walls. Based on the principles of energy conservation, the indoor air temperature can be mathematically expressed, taking into account these variables and their interplay as depicted in Fig. 2. This expression is central to understanding the dynamics of indoor temperature regulation and forms the basis for further exploration and analysis in this study.

$$\rho_a V_{indoor} C_p \frac{dT_{indoor}(\tau)}{d\tau} = a_p F_p(t) - U_w A_w \left[T_{indoor}(\tau) - T_{outdoor}(\tau)\right] \tag{1}$$

Here, ρ_a air density, V_{indoor} volume of air into the room, C_p heat capacity of air, T_{indoor} indoor air temperature, τ time, a_p channel coefficient, F_p water flowrate into heating/cooling system, $T_{outdoor}$ outdoor air temperature, A_w square of the wall, U_w overall heat transfer coefficient for the wall.

To simplify Laplace transforms as presented in Eq. (3), the process typically involves converting the time-domain equation into its corresponding s-domain representation. This conversion facilitates the analysis of systems, particularly in the context of control systems and differential equations. The Laplace transform essentially converts differential equations, which can be complex to solve in the time domain, into algebraic equations in the s-domain, which are simpler to manipulate and solve.

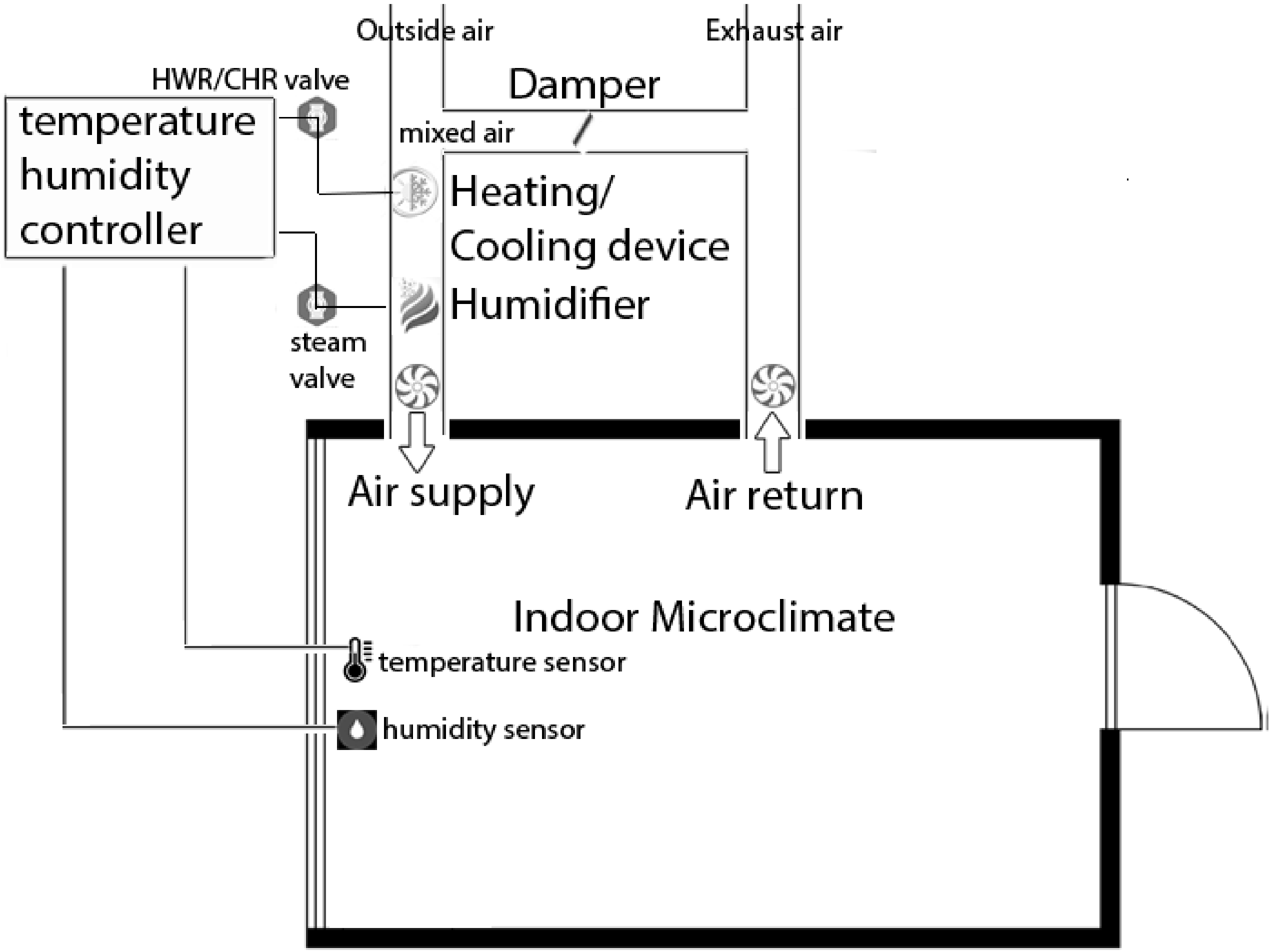

Fig. 2. Schematic diagram of indoor air temperature and humidity control processes in HVAC system.

In the context of the specific Eq. (1) you're referring to, the Laplace transform would take each term of the equation and convert it into its Laplace form. This involves identifying the Laplace transform of each component of the equation – for instance, functions of time, derivatives, and integrals – and representing them in terms of 's', which is the complex frequency parameter in the Laplace domain.

$$\left[\frac{\rho_a V_{indoor} C_p}{U_W A_W} s + 1\right] \cdot T_{indoor}(s) = \frac{a_P}{U_W A_W} F_P(s) + T_{outdoor}(s) \tag{2}$$

Under the assumption that the indoor temperature is not influenced by the outdoor temperature and considering the time delay inherent in the heat transfer process within an indoor environment, the simplification of Eq. (4) can be approached by focusing on the internal dynamics of the system while disregarding external thermal influences.

$$G_{11} = \frac{T_p(s)}{F_p(s)} = \frac{k_{tp} e^{-q_{tp} s}}{t_{tp} s + 1} \tag{3}$$

When considering the relationship between temperature and humidity in an indoor environment, it's essential to acknowledge that changes in humidity can significantly affect air temperature. The operation of a humidifier, by adding moisture to the air, can influence the thermal characteristics of the space. This is due to the latent heat exchange involved in the process of humidification, which can either absorb or release heat, thereby affecting the overall air temperature.

Incorporating the effect of the humidifier on the temperature, typically represented by the temperature Tq affected by the humidification process, the indoor air temperature can be modeled taking into account both the direct heating or cooling effect (through HVAC systems) and the indirect effect of humidification. The relationship can be expressed in a combined form where the temperature equation accounts for the additional variable Tq.

The modified equation would typically include terms representing the heat added or removed by the HVAC system and the change in enthalpy due to humidification. The equation might take a form similar to:

$$G_{12} = \frac{T_q(s)}{F_q(s)} = \frac{k_{tq} e^{-q_{tq} s}}{t_{tq} s + 1} \tag{4}$$

Where, G_{12} Laplace transfer function, F_q flowrate of steam, $t_{tq} = \frac{V_{indoor}}{f_a}$, $k_{tq} = \frac{a_q a_t}{f_a r_a E_p}$.

V. Fuzzy Rules for HVAC Control

In the pursuit of maintaining internal thermal comfort within a specified environment, a controller equipped with fuzzy inference capabilities has been developed. This controller is tasked with calculating the necessary power to sustain the desired thermal conditions. The operational mechanism of this fuzzy controller is based on the inputs of error and error rate of change, which are pivotal in guiding its decision-making process.

The concept of 'error' in this context refers to the deviation between the desired temperature setpoint and the actual temperature observed within the environment, represented as e (measured in degrees Celsius, °C). This error is a critical factor in determining the necessary adjustments required to achieve thermal comfort. Additionally, the controller considers the rate of change of this error over time, which is essentially the first derivative of the temperature variation within a given computational cycle. This rate of change is measured in °C/min and provides insight into the dynamic behavior of the temperature within the environment [47].

The primary challenge addressed by this controller is the accurate determination of the temperature output that should be relayed to the digital-to-analog converter regulator. This regulator then executes the necessary adjustments to align the actual temperature with the desired setpoint. The input variables for this regulator include the aforementioned error e and the rate of change of this error. By leveraging these inputs, the fuzzy inference controller can make nuanced decisions that account for both the current state and the trajectory of the temperature, thereby ensuring efficient and responsive control for maintaining internal thermal comfort.

$$\Delta e = T_{desired}(t) - T_{current}(t) \tag{5}$$

where, $T_{desired}(t)$, $T_{current}(t)$ are the desired and current temperatures in °C and t is the time in minutes.

The rate of temperature change in a given environment, particularly when cooling or heating is involved, is intrinsically linked to the magnitude of the temperature difference between the desired setpoint and the current temperature. This relationship is a fundamental principle in thermodynamics and heating, ventilation, and air conditioning (HVAC) system dynamics.

Mathematically, the rate of temperature change can be expressed through a formula that incorporates the temperature difference as a key variable. The formula typically takes into account not only the temperature difference but also the efficiency and capacity of the heating or cooling system, the thermal properties of the space (like insulation and volume), and external factors such as ambient temperature.

The rate of temperature change (ΔT/Δt), where ΔT is the temperature difference and Δt is the time interval, can be represented as:

$$\Delta e = \frac{e(t_1) - e(t_2)}{t_1 - t_2} \tag{6}$$

In the development of a fuzzy logic controller for temperature regulation, the concept of linguistic fuzzy variables becomes paramount. These variables allow for the characterization of the system's state in a manner that is akin to human reasoning, which is especially useful in systems where precision and complex calculations are less feasible or desirable. In this context, the linguistic fuzzy variables are designed to describe the temperature difference (e) and the rate of temperature change.

The construction of membership functions for these variables is a critical step in the fuzzy logic design process. Membership functions define how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. For this controller, two distinct membership functions are formulated:

Temperature Difference (e): This function maps the temperature difference (e) within the range of -6 to +6 °C. The linguistic identifiers for this membership function include:

Large Positive Deviation (LPD)

Average Positive Deviation (APD)

Small Positive Deviation (SPD)

Zero Deviation (Z)

Small Negative Deviation (SND)

Average Negative Deviation (AND)

Large Negative Deviation (LND)

Rate of Temperature Change: This function represents the rate of temperature change within the range of -6 to +6 °C/min. The same linguistic identifiers (LPD, APD, SPD, Z, SND, AND, LND) are used to describe the rate of change.

These membership functions, as visualized in Fig. 3 for the temperature difference and Fig. 3 for the rate of temperature change, enable the fuzzy logic controller to interpret and respond to various states of the indoor environment. The output parameter value, which is the result of the joint effect of these two membership functions, is determined by the control logic programmed into the fuzzy logic controller. This logic dictates how the controller responds to different combinations of temperature difference and rate of change, guiding the adjustments needed to achieve and maintain the target indoor temperature.

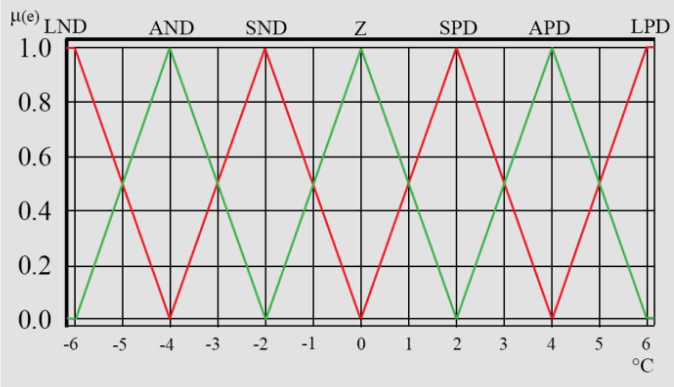

Fig. 3. Linguistic membership functions by the input parameter.

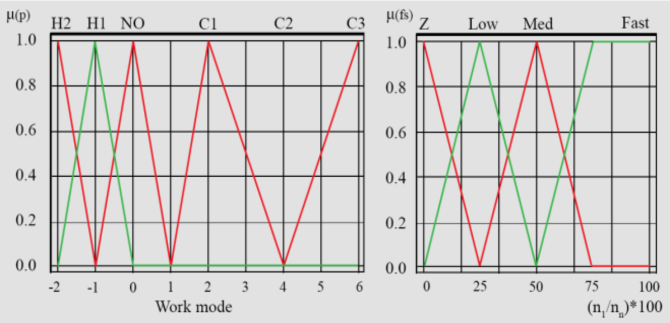

Fig. 4. Linguistic membership functions by output parameter.

Utilizing the established membership functions, as delineated in Fig. 4, the optimal operational mode for the heating and cooling systems within an indoor environment can be determined through fuzzy logic control. This control strategy employs a set of fuzzy variables, each with specific identifiers to represent different levels of heating and cooling required. These variables and their respective identifiers are:

Utilizing the established membership functions, as delineated in Fig. 4, the optimal operational mode for the heating and cooling systems within an indoor environment can be determined through fuzzy logic control. This control strategy employs a set of fuzzy variables, each with specific identifiers to represent different levels of heating and cooling required. These variables and their respective identifiers are:

For Cooling:

Strong Cooling (C3)

Average Cooling (C2)

Slight Cooling (C1)

For Heating:

Heating 1 (H1)

Heating 2 (H2)

For Neutral State:

Without Changes (NO)

In a similar fashion, the control of the fan rotation speed is computed based on a rule base, as visualized in Fig. 4. The fuzzy variables for fan speed are identified as:

High (Fast)

Normal (Med)

Low (Low)

Zero (Z)

The output membership function, represented in Fig. 4, illustrates the processing rule employed in the fuzzy logic system. This rule aggregates the response signals to generate a comprehensive output command. The chosen function in this study is designed to provide an output encompassing two heating levels (H1, H2), three cooling levels (C1, C2, C3), and a normative level (NO). This approach allows for a nuanced response to varying thermal conditions, enabling the system to adaptively modulate the heating or cooling levels, as well as the fan speed, in accordance with the real-time requirements of the indoor environment.

The flexibility of the fuzzy logic control system lies in its ability to interpolate between these defined levels, potentially envisaging scenarios where additional heating or cooling levels could be implemented. This could involve settings that exceed the defined parameters of H2 for extra heating or provide cooling options that are more intense than the levels of C2 and C1, thus catering to a wide range of environmental conditions and occupant comfort preferences.

Table I in the study delineates the application of linguistic variables, which are derived from the process of fuzzification applied to the response signal. This fuzzification process is significantly guided by operator intuition, a crucial aspect in the fuzzy logic control system. The linguistic variables, as defined and used in the system, encapsulate the varying degrees of response required for temperature regulation within the indoor environment.

TABLE I. LINGUISTIC MEMBERSHIP FUNCTIONS BY OUTPUT PARAMETER

		Temperature difference (e)						
		LND	***AND***	***SND***	***Z***	***SPD***	***APD***	***LPD***
Rate of temperature change	**LND**	C3	C3	C2	C1	NO	NO	H1
		Fast	Fast	Med	Slow	Z	Z	Med
	AND	C3	C2	C2	C1	NO	NO	H1
		Fast	Med	Med	Slow	Z	Z	Med
	SND	C3	C2	C1	C1	NO	NO	H1
		Fast	Med	Slow	Slow	Z	Z	Med
	Z	C2	C1	C1	NO	NO	H1	H1
		Med	Slow	Slow	Z	Z	Med	Med
	SPD	C1	C1	NO	NO	H1	H1	H2
		Slow	Slow	Z	Z	Med	Med	Fast
	APD	C1	C1	NO	NO	H1	H2	H2
		Slow	Slow	Z	Z	Med	Fast	Fast
	LPD	C1	C1	NO	NO	H2	H2	H2
		Slow	Slow	Z	Z	Fast	Fast	Fast

e	+ very cold	conditioner
	- very hot	
Δe	+ heat consumption	ventilator
	- cold consumption (heat output)	

VI. EXPERIMENTAL RESULTS

In this segment, we present the modeling and simulation results for a fuzzy Proportional-Integral-Derivative (PID) controller, specifically applied to the task of temperature regulation. The scenario begins with the assumption that the initial temperature within a room is not at an optimal level, thus necessitating adjustment. Upon setting a target temperature, the controller initiates its operation to achieve this desired thermal state. For the purpose of simulating this process, a reference input signal, indicative of the temperature difference to be addressed, is employed. Let us consider a scenario where the temperature difference between the internal environment and the external medium is set at 5 °C. Consequently, a step signal, denoted as r(k)=5, is introduced at the initiation of the simulation (time = 0 t=0).

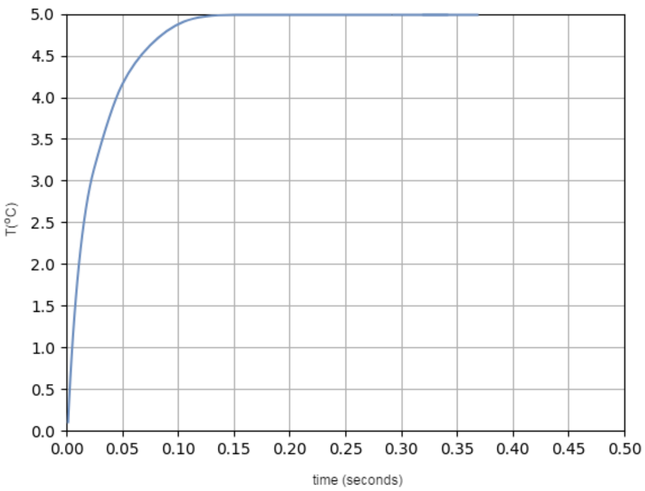

Fig. 5. System output response to step input.

The resultant simulation output of the temperature control system is depicted in Fig. 5. Analyzing the figure, we observe key performance metrics such as the time constant τ=0.033 seconds) and the settling time (t=0.092 seconds). These metrics are indicative of the controller's responsiveness to the input signal. Notably, the control system exhibits a rapid reaction time, characterized by a high rate of increase in response to the step change in temperature.

Additionally, the response dynamics of the system demonstrate the absence of overshoot, which is a desirable attribute in control systems, indicating precision and stability in reaching the target state without exceeding it. Moreover, the steady-state error is observed to be zero at the point where the control process stabilizes. This absence of steady-state error signifies that the proposed fuzzy PID control system effectively attains the desired temperature without deviation, thereby exemplifying its excellent performance. The system not only responds swiftly but also maintains control accuracy and stability, ensuring that the desired room temperature is achieved efficiently and reliably.

In the pursuit of maintaining internal thermal comfort within a specified environment, a controller equipped with fuzzy. Upon integrating these linguistic variables with the output membership function and subsequent de-fuzzification process, a distinct and actionable control signal is generated. This signal is pivotal in the fuzzy logic control system as it dictates the specific control actions to be undertaken by the heating and cooling systems. The control signal, in essence, represents the required level of heating or cooling, quantified in a range that typically includes values such as [−2, −1, 0, 1, 2, 3, ...]. These values correspond to the degrees of heating or cooling necessary to maintain or achieve the desired indoor temperature.

For instance, negative values (e.g., -2, -1) might indicate the need for cooling at various intensities, while positive values (e.g., 1, 2) suggest varying levels of heating. A zero value (0) would imply that no change is needed, maintaining the current state. The higher the absolute value, the more intense the heating or cooling action required.

The transformation of fuzzy inputs into a clear and quantifiable control signal through de-fuzzification is a crucial step, enabling the practical application of fuzzy logic theory in real-world control systems. This process ensures that the inherently vague and subjective nature of linguistic variables is translated into precise control actions, effectively bridging the gap between human-like reasoning and mechanical system control.

This figure elucidates how the controller's command, formulated based on the output data, is calculated and subsequently dispatched to the requisite device. This command is integral to modifying the air temperature within the room, showcasing the controller's active role in environmental regulation.

Further examination is presented in Fig. 6, which delineates the automatic adjustment process of the PID parameters. From these observations, it can be conclusively stated that the fuzzy PID control methodology effectively modifies the traditional PID controller parameters. This adaptability optimizes the control performance, ensuring that the system is responsive and stable, thereby achieving the desired environmental conditions with enhanced precision.

Fig. 6 presents a graphical depiction of the variations in carbon dioxide (CO2) levels over the course of a single working day in January 2021. This visualization provides insightful data on how human presence and activities in a workplace environment impact indoor air quality, particularly concerning CO2 concentration.

At the commencement of the working day, the CO2 concentration was observed to be low. However, a notable increase in the level of CO2 was recorded around 9:00 AM, corresponding with the arrival of employees at the workplace. This sharp rise in CO2 levels is attributable to the increased number of people, and hence, respiration rates within the enclosed space.

Subsequently, the efficiency of the air quality control system is evidenced as the CO2 levels are reduced to below 1000 parts per million (ppm). This reduction signifies the effective functioning of the ventilation or air purification system in managing and maintaining optimal air quality despite the increased occupancy.

An interesting variation is observed during the lunch hour, starting from 13:00 and lasting until 14:00. During this period, there was a discernible decrease in CO2 concentration to approximately 600 ppm. This reduction can be attributed to the opening of windows, allowing for enhanced natural ventilation and dilution of indoor CO2 levels. Post-lunch, as employees resumed their activities, the CO2 concentration experienced an immediate upsurge, eventually stabilizing at a comparatively steady level. This pattern suggests a consistent occupancy and activity level in the afternoon hours.

Finally, after 18:00, coinciding with the end of the workday and the departure of the employees, a decrease in CO2 levels was again observed. This trend aligns with the reduced human presence in the building, leading to lower respiration rates and thus, lower CO2 emission within the indoor environment. This diurnal pattern in CO2 levels highlights the direct correlation between human occupancy and indoor air quality, as well as the critical role of effective air quality management systems in maintaining a healthy indoor environment.

Monitoring the level of CO2 in indoor environments is crucial, distinctly different from the regulation of relative humidity and temperature, which are typically maintained within a specific range. The dynamics of CO2 concentration, particularly in scenarios where the air conditioning system is operational or when natural ventilation is enabled, are critical for indoor air quality (IAQ) management.

When the air conditioning is active or when the area is naturally ventilated (referred to as the air conditioning region being 'open' or 'free'), there is a noticeable decrease in CO2 levels within the room. This effect brings the CO2 concentration down to a lower, more desirable setting. In such scenarios, the CO2 levels inside the room fluctuate within a comparative range. However, it is important to note that standard deviation, a common statistical measure, may not adequately represent the effectiveness of air quality rate control strategies in managing CO2 levels.

Consequently, the internal temperature is often utilized as a more reliable parameter for assessing the performance of IAQ controllers. Fig. 7 in the study highlights the maximum monthly internal CO2 concentration observed. The findings indicate that the peak daily CO2 concentration does not exceed 1100 parts per million (ppm). This concentration level, while being the highest observed, is still within a range that is considered not harmful to human health and does not persist for prolonged durations.

Such insights are crucial in understanding the efficacy of IAQ control systems in maintaining CO2 concentrations at safe levels, ensuring a healthy indoor environment. This focus on CO2 levels, alongside temperature and humidity, forms a comprehensive approach to IAQ management, safeguarding both comfort and health within indoor spaces.

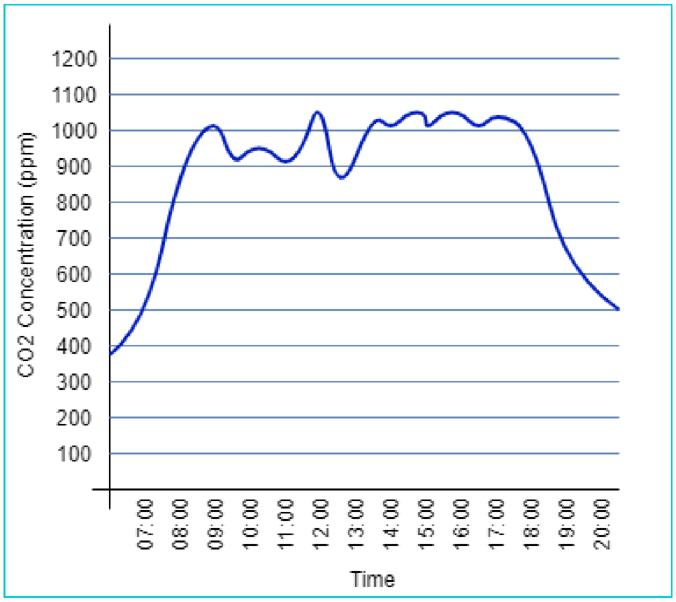

Fig. 6. Indoor CO2 concentration level.

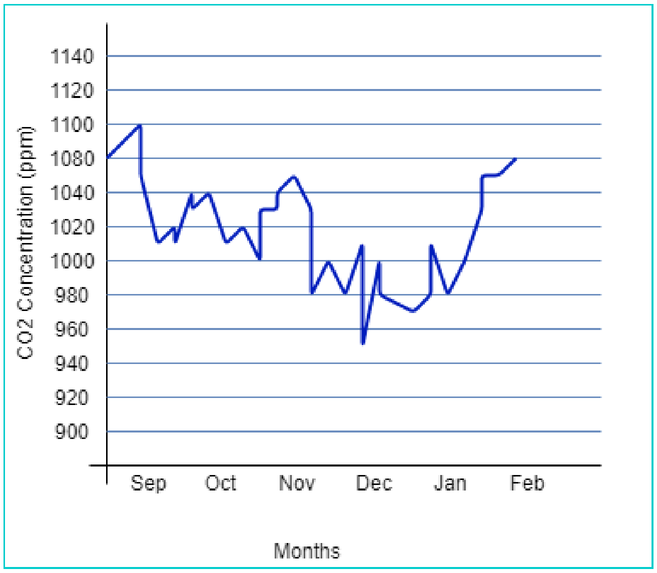

Fig. 7. Indoor CO2 concentration level for six months.

VII. Discussion

In the Discussion section of this paper, we critically examine the findings from our study on the implementation of a fuzzy PID controller for indoor climate control, with a particular focus on temperature regulation and CO2 level monitoring.

Temperature Control and CO2 Monitoring: Our research underscores the significance of precise temperature control and effective CO2 monitoring in indoor environments [48]. The implementation of a fuzzy PID controller demonstrated substantial efficacy in maintaining the desired temperature levels. This outcome is particularly noteworthy given the dynamic nature of indoor environments, where temperature can be influenced by various factors such as human occupancy, external weather conditions, and heating or cooling systems [49]. The fuzzy logic aspect of the controller, with its ability to handle imprecise inputs, proved crucial in adapting to these dynamic conditions.

Moreover, the CO2 level monitoring presents an additional layer of complexity. Unlike temperature and humidity, which are regulated within a defined range, CO2 levels require continuous monitoring to ensure they remain within safe limits. The study’s findings reveal that the integration of ventilation systems or natural air flow significantly impacts the reduction of CO2 levels, emphasizing the importance of adequate ventilation in indoor spaces for air quality management [50].

Performance of the Fuzzy PID Controller: The fuzzy PID controller's performance, particularly in the context of its rapid response and stability, is a highlight of this study. The controller's swift adaptation to changes in temperature and its ability to stabilize the indoor climate without overshooting the desired parameters underscore its efficiency [51]. The automatic tuning of PID parameters (kp, ki, and kd) according to fuzzy logic control rules further enhances the system's responsiveness and accuracy. This adaptability is crucial in scenarios where indoor conditions fluctuate frequently.

Limitations and Future Work: Despite the positive outcomes, there are limitations to this study that open avenues for future research. The study primarily focuses on a controlled environment, and extending these findings to more varied and complex real-world scenarios would be beneficial [52]. Further research could explore the integration of additional environmental factors, such as humidity levels and air pollutants, into the control system for a more comprehensive approach to indoor climate control.

Additionally, the study’s reliance on specific models and simulation tools may limit its generalizability. Future research could look into the application of the fuzzy PID controller across different models and simulation environments to validate its effectiveness further.

Implications for Indoor Air Quality (IAQ) Management: The findings have significant implications for IAQ management. Maintaining optimal levels of temperature and CO2 is not only essential for comfort but also for health. Elevated CO2 levels can lead to decreased cognitive function and increased health risks. Therefore, the ability of the fuzzy PID controller to effectively manage these parameters is crucial [53]. The insights gained from this study could inform the design and implementation of HVAC systems in various settings, from residential buildings to office spaces and public facilities.

Environmental and Energy Considerations: Environmental sustainability and energy efficiency are other critical aspects highlighted by this research. The intelligent control of HVAC systems, as demonstrated by the fuzzy PID controller, can contribute to energy conservation by optimizing the operation of heating and cooling systems. This optimization not only reduces energy consumption but also minimizes the environmental footprint of buildings.

The study presents a significant contribution to the field of HVAC system control, particularly in the areas of temperature regulation and CO2 monitoring. The implementation of a fuzzy PID controller demonstrates a promising approach to managing indoor climate conditions, balancing comfort, health, and energy efficiency. Future research expanding on these findings and addressing the identified limitations could pave the way for more sophisticated and environmentally sustainable indoor climate control solutions.

VIII. Conclusion

In conclusion, this research paper has made a significant contribution to the field of indoor climate control by exploring the efficacy of a fuzzy Proportional-Integral-Derivative (PID) controller in regulating temperature and monitoring carbon dioxide (CO2) levels in indoor environments. The findings of this study underscore the importance of precise environmental control in indoor settings, not only for occupant comfort but also for health and energy efficiency. The implementation of the fuzzy PID controller has demonstrated a commendable level of adaptability and accuracy in maintaining desired temperature levels, even in the face of varying indoor conditions and external influences. The integration of fuzzy logic with traditional PID control has enhanced the system's ability to handle ambiguous and fluctuating data, a common characteristic in real-world environments. Furthermore, the focus on CO2 level monitoring, a critical component of indoor air quality, highlights the necessity of continuous surveillance of environmental parameters beyond temperature and humidity.

A key takeaway from this research is the controller's capability to rapidly respond to changes in the indoor environment and stabilize the conditions without overshooting the set parameters. This responsiveness is crucial in ensuring a consistent and comfortable indoor climate. Additionally, the study's insights into the automatic tuning of PID parameters based on fuzzy logic control rules contribute to the broader understanding of intelligent control systems in HVAC applications. Despite its successes, the study acknowledges the need for further research in more diverse and complex settings to validate the generalizability of the findings. Future investigations could also delve into the integration of other environmental factors and explore the potential for advanced predictive control mechanisms.

In essence, this research provides a valuable framework for the development of sophisticated and efficient climate control systems, offering significant benefits in terms of occupant well-being, environmental sustainability, and energy conservation. The implementation of such intelligent control systems is poised to play a pivotal role in the evolution of smart building technologies and the advancement of indoor environmental quality.

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Efficient Compression for Remote Sensing: Multispectral Transform and Deep Recurrent Neural Networks for Lossless Hyper-Spectral Imagine

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***Abstract*—Remote sensing technologies, which are essential for everything from environmental monitoring to disaster relief, enable large-scale multispectral data collection. In the field of hyper-spectral imaging, where high-dimensional data is required for precise analysis, effective compression techniques are critical for transmission and storage. In the field of hyper-spectral imaging, the development of efficient compression techniques is critical because datasets containing high-dimensional information must be transmitted and stored efficiently without sacrificing analytical precision. The paper presents advanced compression techniques that combine deep Recurrent Neural Networks (RNNs) with multispectral transforms to achieve lossless compression in hyper-spectral imaging. The Discrete Wavelet Transform (DWT) is used to efficiently capture spectral and spatial information by utilizing the properties of multispectral transforms. Simultaneously, deep RNNs are used to model the hyper-spectral data with complex dependencies, allowing for sequential compression. The overall compression efficiency that is increased by the integration of spatial and spectral information allows for reduced storage requirements and improved transmission efficiency. Python software is used to implement the proposed model. When compared to Liner Spectral Mixture Analysis (LSMA) based compression, Spatial Orientation Tree Wavelet (STW)-Wavelet Difference Reduction (WDR), and DPCM, the proposed DWT-RNN-LSTM method has a better PSNR value of 45 dB and a lower MSE of 7.50%. Adaptive compression methods are presented in order to dynamically adapt to various data properties and ensure application in various hyperspectral scenes. Studies on hyper-spectral images of various sizes and resolutions demonstrate the approach's scalability and generalization, as well as the utility and adaptability of the proposed compression framework in a variety of remote sensing scenarios.**

Keywords*—Multi-Spectral transform; lossless compression; hyper-spectral data; deep recurrent neural network; compression algorithms

I. Introduction

Spectral imaging uses multiple bands across the electromagnetic spectrum, obtaining data simultaneously from imaging and spectroscopy. Multispectral remote sensors capture data from three to fifteen broad wavelengths, while hyper spectral sensors capture multiple bands. In contrast, several spectral bands spanning a wide wavelength range of 400–2500 nm are concurrently captured by hyper spectral (HS) remote sensors [1]. Spectrophotometry is the foundation of the hyperspectral imaging method. For every spatial area, numerous wavelengths and bands of data from images are collected. With the use of this data, a hyperspectral cube is produced, with the third dimension representing spectral content and the other two representing the location's spatial extent. Materials with varied qualities can be distinguished from one another thanks to the spectral signature, which is the result of particle scattering and molecule absorption [2]. Among the uses for hyperspectral remote sensing include criminal investigation, forecasting weather, agriculture, the food sector, and the medical field [3]. But this richness of information comes at a high memory cost because hyperspectral imagery generates a large amount of data that needs to be stored. These images' extreme richness stems from their high spectral dimensionality, which includes a wide range of spectral channels that capture subtle details about the scene or object under study. Since each pixel contains 16- or 12-bit data, a single HIS dataset might be hundreds of gigabytes (MBs) in size. The range of pixel values can range from a hundreds to millions, and the range of band numbers can be as high as 22 [4]. Compared to RGB and multispectral images, hyperspectral imaging (HSI) has a higher number of bands and a finer spectral resolution [5]. Hyperspectral images can contain dozens or even hundreds of spectral bands, whereas multispectral images usually only have a few. Over the past few decades, hyperspectral imaging has extended beyond traditional ground-based computer vision applications and shown great potential in a variety of fields, including recognizing faces, chemical engineering, farming, biology, and archaeological research. Its uses include material identification, record or ink aging, pen authentication, visual similarity ink differentiation, and documentation preservation.

With its ability to capture and analyze a wide range of contiguous spectral bands across the electromagnetic spectrum, this advanced imaging technology has become indispensable in a variety of fields, including remote sensing, agriculture, healthcare, and environmental monitoring. Hyperspectral imaging in environmental science allows for the accurate identification and tracking of ecological variables, which helps with well-informed conservation decision-making. It helps with disease detection, crop health assessment, and efficient resource allocation in agriculture. Hyperspectral imaging aids in diagnosis in the medical field by providing in-depth understanding of tissues and biological processes. Additionally, its uses in remote sensing enable businesses to obtain comprehensive data about the surface of the Earth, improving resource management and disaster response. Hyperspectral imaging's versatility and depth of data continue to spur innovation, making it a vital tool for a wide range of academic and professional projects.

One of the main concerns of compression algorithms that aim to reduce data redundancy is the difficulty of analysing large hyperspectral images (HSI) while preserving important information. Data redundancy and compression ratios are crucial in the field of multispectral images, such as Hyperspectral Imaging (HSI). Because redundant information gives compression algorithms plenty of opportunities to take advantage of similarities and patterns, high data redundancy in these images frequently results in elevated compression ratios. Multispectral images exhibit redundancy in four different flavours, each of which has a unique impact on the compression process. Similarities between spectral bands, where adjacent bands may convey similar information, give rise to spectral redundancy. Since neighbouring pixels in multispectral imagery frequently show similarities, spatial redundancy results from redundant information within the same spectral band of images. When thinking about sequential images over time, temporal redundancy is introduced, capturing redundant information across different moments. Lastly, inter-band redundancy adds to the overall redundancy landscape by involving correlations between various spectral bands. It is essential to comprehend and control these different types of redundancy when optimizing compression techniques for multispectral imagery. First, statistical redundancy is analysed through symbol probability, which is commonly done using entropy coding. Second, if pixel information can be partly acquired from nearby pixels and is reduced by transformations, spatial redundancy depends on intraband correlation. Thirdly, spatial decorrelation eliminates spectral redundancy, also known as interband correlation, which results from strong correlations between adjacent bands in hyperspectral images [6].

Finally, visual redundancy uses data quantization for compression based on visual redundancy, which is influenced by the insensitivity of the human eye to high frequencies. Compression methods are divided into two categories: two-dimensional and three-dimensional. They utilize correlations between or within bands [5]. Redundancy in multispectral images can occur in four ways: spectral redundancy, spatial redundancy, temporal redundancy, and inter-band redundancy. These factors complicate compression dynamics and require efficient management to develop compression strategies tailored to the unique properties of multispectral imagery. In order to achieve lossless compression, this research study investigates an advanced method of hyperspectral image compression that integrates deep recurrent neural networks (RNNs) with multispectral transforms. The purpose of this integration is to take advantage of the complex temporal dependencies and spatial-spectral correlations found in hyperspectral images in order to improve compression performance while maintaining crucial data for further analysis. DWT and PCA are two multispectral transforms that are initially utilized to take advantage of the spatial-spectral redundancies that are naturally present in hyperspectral data. In order to prepare the way for later compression stages, these transforms seek to decorrelate spectral information. To capture complex spatial correlations across the different spectral bands, deep recurrent neural networks which are well-known for their capacity to represent long-range dependencies are introduced as a building block. A synergistic approach to addressing the particular challenges posed by hyperspectral image compression is ensured by the seamless integration of deep RNNs and multispectral transforms. The aim of this work is to create an entire framework that best utilizes the advantages of deep RNNs and multispectral transforms while also achieving lossless compression and faithfully reconstructing the original hyperspectral image. The technique aims to achieve higher ratios without compromising the integrity of important spectral information by adaptively choosing and combining parameters according to the unique features of the hyperspectral data. This research presents a novel method for hyperspectral image compression, adding to the ever-changing field of remote sensing. Enhancing the efficacy and precision in remote sensing applications is possible through the integration of deep recurrent neural networks and multispectral transforms, which presents a promising solution to the problems posed by managing large volumes of hyperspectral data.

This study’s key contributions are as follows:

- Development of an advanced compression method for hyperspectral images that uses temporal dependencies and spatial-spectral correlations to seamlessly combine deep recurrent neural networks with multispectral transforms.
- Utilizing Discrete Wavelet Transform (DWT), to optimize the data for further compression stages in order to decorrelate spectral information.
- Enhancing the compression performance by capturing and taking advantage of intricate spatial correlations across the different spectral bands using deep RNN, more especially Long Short-Term Memory (LSTM) networks.
- Integrated spectral and spatial information using deep RNNs and multispectral transforms. This integration seeks to improve compression efficiency by utilizing

the correlation between adjacent pixels and spectral bands.

The structure is organized like the following. Section II explores works that are similar to the current study by exploring into the body of previous literature in the topic. After that, the problem statement is outlined in Section III, along with the particular difficulties that the study attempted to solve. The methodology of the suggested model, including its numerous components and methods, is expounded upon in Section IV. Next, a thorough discussion is started in Section V, which provides a concise summary of the results. Section VI provides a conclusion of the research outcome and considerations for further research.

II. Related Works

Li et al. [7] suggested a proposal for remote sensing multispectral image compression using convolution neural networks and multispectral transforms. The benefits of TD, such as Nonnegative Tucker Decomposition, can be used to compress multispectral images. CNN with NTD is the foundation of a low-complexity compression method for multispectral images that was developed. A novel spectrum transform was employed, leveraging CNNs to convert the three-dimensional spectral tensor from a large to small-scale version. The initial and rebuilt three-dimension spectral tensor in self-learning CNNs were minimized in order to produce the optimized spectral tensor for small scale. To increase computation efficiency, the NTD resources only allot the small-scale three-dimension tensor. The result shows that the computation efficiency improved by 49.66% by sacrificing only 0.3369 dB compared to NDT. The drawback is the essential to implement a complex learning network to reduce computational costs.

Cabronero et al. [8] Proposed High-Efficiency Lossless Compression of Spectral Decorrelation. To obtain as many HSI scenes on the ground as possible, data reduction is a crucial tool. Simultaneously, space borne devices' energy and hardware limitations place restrictions on the complexity of workable compression algorithms. In this study, only lossless compression is taken into consideration to prevent any distortion in the analysis of the HSI data. The goal of this work is to determine the optimal trade-off between complexity and compression for high-spatiality HSI compression. The goal of this work is to determine the best possible trade-off between complexity and compression for high-spatiality images (HSI) compression. Results regarding the execution time and compression performance are obtained for a collection of 47 HSI scenes generated by 14 distinct sensors during actual remote sensing missions. The results obtained indicate that the FAPEC algorithm provides the best trade-off, assuming that there is only a finite amount of energy available.

Dua et al. [9] suggested a lossless prediction-based multi-temporal image compression method in this research. It greatly reduces the size of the time-lapse hyperspectral image by eliminating temporal correlations. It uses a linear combination of pixels from previously estimated spectral and temporal bands to predict the target image's pixel value. The RLS filter is used to update the weight matrix that is used in the prediction. The best number of bands to choose for prediction, the relative strength of each correlation, and the bit-rate efficiency of the method are all shown by the experimental results. According to the findings, adding temporal correlations lowers the bit-rate by 24.07%, and the model optimizes the bits per pixel by 18.15% when compared to the most advanced technique. The disadvantage is that designing a universally applicable solution becomes difficult when automating the entire process and dealing with a variety of datasets and scenarios. Furthermore, the process of creating an automatic model to determine the number of temporal prediction bands might encounter challenges in precisely encapsulating the subtleties of different datasets, which could result in less-than-ideal performance in specific scenarios.

Deng at al. [10] proposed a model, utilizing Generative Neural Networks for Learning-Based Hyperspectral Image Compression. The research presented an alternative method of HSI compression using a GNN, which uses a random latent code to learn the distribution of probability of the actual data. To do this, it's necessary to must define a family of densities and identify the one that minimizes the difference between the actual data distribution and this family. The HSI is then represented by the well-trained neural network, and the complexity of the GNN controls the compression ratio. Additionally, the latent code can be made secret by encrypting it with a random distribution digit embedded in it. To show the GNN potential in resolving compression issues of images in the field of HSI, experimental examples are provided. This work presents a novel neural network-based compression technique and opens up a wide range of new research avenues. Other structures can be added to increase the compression ratio is the major drawback. Additionally, since the neural network can be thought of as a representation of the HSI, the GNN can be used directly for many tasks, including classification, by manipulating its layer to match the classification label.

Makarichev et al. [11] suggested a Quality Controlled Lossy Compression of Three-Channel Remote Sensing data via Discrete Atomic Transform, three-channel RS images are utilized. It is shown how varying and controlling the maximal absolute deviation can affect the quality of images compressed by DAT. Additionally, there is a strict relationship between this parameter and more conventional metrics like PSNR and RMSE, which can be adjusted. Additionally, it is demonstrated that the depths of the various DAT variants vary. A variety of perspectives are used to compare their performances, and transform depth suggestions are provided. The disadvantage is that DAT-based compression cannot be extended to RS data or to other practical tasks like classification of crops, forest cut monitoring, etc.

Grassa et al. [12] proposed a Compression of Hyperspectral Data Using a Fully Convolutional Autoencoder. A new deep convolutional auto encoder architecture-based Spectral Signals Compressor Network. Comprehensive tests were carried out on a variety of multi/hyperspectral and RGB datasets, demonstrating significant gains over baselines and outperforming conventional JPEG family algorithms. The outcomes demonstrate the effectiveness of SSCNet in obtaining better compression ratios and reconstructing spectral signals, especially showing resilience when dealing with data types larger than 8 bits. Moreover, thorough assessment employing PSNR, SSIM, and MS-SSIM standards consistently demonstrates SSCNet's superiority over current techniques, confirming its mastery of spectral signal compression. The efficacy and accessibility of the framework across RGB, multi spectrum, and hyperspectral sources were proven through extensive experiments on multiple benchmark datasets, which also reported a high compression ratio achieved and an excellent reconstruction.

Changcheng et al. [13] suggested a matrix with an invertible method to eliminate spectral redundancy and improve bit allocation inside the structure. To reduce redundancy, the method combines the DWT's lifting scheme with other strategies like SPIHT coding. The experimental results highlight how well the suggested algorithm performs in lossless compression when compared to well-known techniques. When compared to the previously mentioned algorithms, the results show a significant average compression ratio improvement of roughly 73.6 % respectively, using the JPL Canal test image as a benchmark dataset.

Leo et al. [14] proposed Hyperspectral image compression without losses with recurrent neural networks. The spectral and spatial resolution of hyperspectral images are constantly rising due to the rapid growth of hyperspectral sensor technology, which in turn is causing the scale of hyperspectral data to grow exponentially. Hyperspectral compression with no loss technology is currently at a standstill. At the same time, the emergence of machine learning has given us fresh concepts. Consequently, the application of deep learning to the lossless compression of hyperspectral images is examined in this paper. Given that the DPCM method is inadequate for forecasting spectral band information, a deep (RNN) is used in the proposed C-DPCM-RNN method to enhance the conventional DPCM method and boost the model's capacity for generalization and prediction accuracy. The ultimate experimental outcome demonstrates that C-DPCM-RNN performs better.

Among the difficulties in compressing multispectral images from remote sensing are the need for novel ways to deal with computational complexity, trade-offs between complexity and compression, the need for universality in compression solutions, and the limitations of existing compression techniques in handling a variety of datasets and real-world applications. Multi-temporal image compression challenges include the need to address the limitations of discrete atomic transform (DAT) in order to extend compression methods to other remote sensing data types and useful applications, as well as the development of globally applicable solutions for a variety of datasets and scenarios. New approaches are needed to address these issues and improve the effectiveness and versatility of compression methods in order to improve the state of multispectral image compression.

III. PROBLEM STATEMENT

Because of the growing amount of hyperspectral imaging data in remote sensing, the previously mentioned literature identifies common issues with storage, transmission, and computational handling. Traditional compression techniques do not handle the complex temporal dependencies and spatial-spectral correlations found in hyperspectral images. To achieve lossless compression, an advanced compression strategy combining deep recurrent neural networks and multispectral transforms must be established. Some of the challenges are the complex spatial-spectral nature of hyperspectral data, the need for computational efficiency, particularly in real-time applications, the need to record and maintain temporal dependencies, adaptability across diverse datasets, and the need for lossless compression to retain critical information [15]. Resolving these issues is critical for improving remote sensing capabilities and ensuring the preservation of hyperspectral data for applications such as agriculture, disaster relief, and environmental monitoring, among others. The proposed method aims to provide a comprehensive response by optimizing hyperspectral data utilization in ways that are both useful and resource efficient.

IV. PROPOSED METHODOLOGY FOR EFFECTIVE LOSSLESS HYPER-SPECTRAL IMAGE COMPRESSION

The proposed methodology of this research involves data collection procedure entails obtaining hyper-spectral images, and to improve contrast throughout the spectral bands, histogram equalization is used for image pre-processing. Consistent contrast enhancement is ensured by the adaptability of histogram equalization to multispectral data. This allows for easier compression in the future and balanced information representation. The impact of compression on performance is assessed using pertinent metrics, and parameters are adjusted based on the requirements of the compression model and the characteristics of hyper-spectral data. The pre-processing step incorporates the histogram equalization seamlessly before multispectral transforms are applied and data is fed into a Deep Recurrent Neural Network (DRNN). The process is essential for preserving information fidelity and optimizes compression by emphasizing subtle features. To efficiently capture spatial-frequency information, the compression pipeline incorporates the DWT. The core of DWT is multi-resolution analysis and sub-band coding, which improve compression in conjunction with DRNN and multispectral transforms. The recurrent nature of the DRNN architecture, which propagates historical information through hidden state vectors, is highlighted in detail. Long-short term memory cells are used in the architecture to provide enhanced memory capabilities and selective information retention through gates, helping to overcome issues like gradient vanishing or exploding Compared to conventional compression techniques, this all-encompassing strategy provides a more holistic representation of the hyper-spectral data and may result in improved compression performance without compromising analytical precision. Furthermore, by employing sophisticated neural network architectures, the model can be made adaptive and learn from the data, which lets it adapt dynamically to various hyper-spectral scene types and maximize compression effectiveness. The block diagram of the proposed methodology is given in the below Fig. 1.

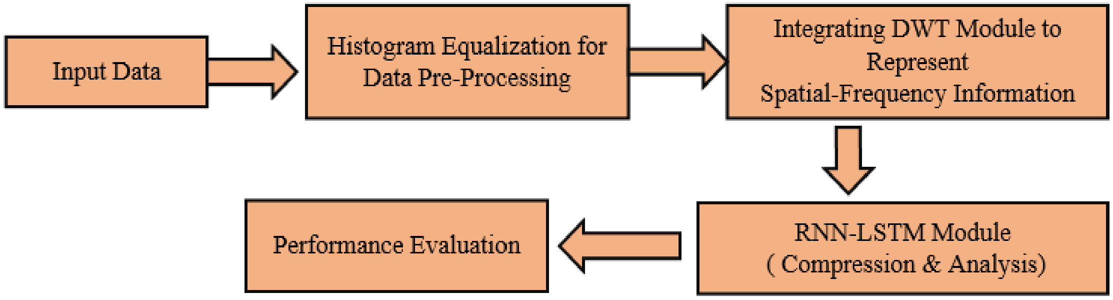
Input Data
Histogram Equalization for Data Pre-Processing
Integrating DWT Module to Represent Spatial-Frequency Information
RNN-LSTM Module (Compression & Analysis)
Performance Evaluation

Fig. 1. Overall block diagram of the proposed methodology.

A. *Data Collection*

Indian Pines hyperspectral datasets in [16] were utilized in order to validate the efficiency of the proposed method. The Indian Pines dataset is used for hyperspectral image compression. The input data is made up of 145x145 pixel hyperspectral bands covering a single landscape in Indiana, US (Indian Pines data set). The dataset of Indian Pines is gathered by the AVIRIS sensor. The dataset comprises resolution of 20 m and 220 spectral bands spanning from 0.4 to 2.5 µm.

B. *Image Pre-processing using Histogram Equalization*

By increasing the contrast of hyper-spectral images, histogram equalization helps to highlight subtle features and may even improve the performance of subsequent compression methods. Consistent contrast enhancement across all spectral bands is ensured by its adaptability to multispectral data, which helps with compression and promotes a more balanced information representation [17]. Histogram equalization supports lossless compression by avoiding information loss brought on by certain characteristics in the original images being difficult to see. Histogram equalization's effect on compression performance should be assessed using pertinent metrics, and parameters should be fine-tuned in accordance with the demands of the compression model and the unique properties of hyper-spectral data. A comprehensive strategy for improving the general quality and efficacy of compression in hyper-spectral imaging is ensured by fully integrating into the pre-processing procedure prior to the application of multispectral transforms and data feeding into the deep recurrent neural network. Histogram Equalization allows for more contrast to be obtained from a smaller localized intensity differential. It seeks to improve the picture's visual attractiveness and ease of analysis. The intensity spreading values of a picture can be seen as arbitrary numbers, ranging from 0 to S-1. The term "random calculation" can also refer to the accompanying cumulative distribution function. The likelihood that an arbitrary value will be assigned a value that is less than or equal to a given value is defined by this function.

Denote the input image f as an array of numerical pixels with intensities values within the range of 0 to S − 1, where S is the intensity probability value. Additionally, q denotes regularized histogram of the primary image (f). Eq. (1) represents the general formula for q and g.

$$qn = \frac{number\ of\ pixels\ with\ intensity\ n}{total\ number\ of\ pixels} \quad \text{n=0, 1 …, L-l} \qquad (1)$$

Eq. (2) represents the histogram equalization of the image.

$$h_{i,j} = flor(S-1)\sum_{n=0}^{f_{i,j}} qn \qquad (2)$$

The flor (.) changed to the closest down integer as a result. This is equivalent to applying the following Eqn. (3) to the values of the densities, k, of 'f ':

$$R(k) = flor(S-1)\sum_{n=0}^{k} qn \qquad (3)$$

This conversion was inspired by considering the densities for f and h as continuous arbitrary values T, H over a time spanning from 0 to L − 1, where Z is a variable. Eq. (4) represents intensity formula is given below.

$$H = R(T) = (S-1)\int_0^x q(x)dx \qquad (4)$$

where, q(x) is the probability intensity formula for g. R is the product of T's collective distribution values and product of (S-1). It will be easier to suppose that the variable U is differentiable and invertible. While the function U(X) denotes T, which is normally distributed.

C. *Integrating Discrete Wavelet Transform*

In 1976, Crochiere introduced sub-band coding for the first time, which laid the groundwork for the discrete wavelet transform [18]. Pyramidal coding, also referred to as multi-resolution analysis, is a method that Burt defined in 1983 and is strikingly similar to sub-band coding [19]. Later, Vetterli and Le Gall eliminated the redundant elements from the pyramidal coding scheme and made some adjustments to the sub-band coding scheme. The system is able to effectively capture and represent the spatial-frequency information present in remote sensing data by adding DWT to the compression pipeline. The combination of DRNN and multispectral transforms improves compression even more, preserving complex features and patterns in hyper-spectral images. This integration opens the door for more precise and efficient downstream analysis in addition to optimizing the transmission and storage of remote sensing data. The combination of these cutting-edge methods is leading the charge in pushing the limits of compression techniques in the context of hyper-spectral imaging, which presents a promising path for improved data management and analysis in remote sensing applications.

The primary signal in DWT is passed through a half-band digital low-pass filter with an impulse response of h[n]. Eq. (5) illustrates the convolution of the signal.

$$y[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k].h[n-k] \qquad (5)$$

By transferring the signal (y[n]) through a half-band low-pass filter, all frequencies higher than half of the primary signal's peak frequency are eliminated. The Nyquist's rule states that half of the samples can be removed. As indicated by Eq. (6), this process involves down sampling (or subsampling) the low-pass filter's output by two.

$$z[n] = \sum_{k=-\infty}^{\infty} h[k].\, y[2n-k] \qquad (6)$$

This process, which makes up one level of decomposition in DWT, can be mathematically expressed using Eq. (7) and Eq. (8) in which the output of the high and low-pass filters following down sampling is denoted by $z_{high}[k]$ and $z_{low}[k]$.

$$z_{high}[k] = \sum_n y[n].\, g[2k-n] \qquad (7)$$

$$z_{low}[k] = \sum_n y[n].\, h[2k-n] \qquad (8)$$

Sub-band coding is the name for this type of decomposition, which doubles frequency resolution and halves time resolution. It can be repeated for additional decomposition by filtering the low-pass filter's output.

The output of DWT is [p3.q3.q2.q1], as shown in Fig. 2. The frequency specifications of the primary signal and its filters are linked to the decomposition levels for DWT. Ultimately, the original signal's DWT is acquired by concatenating all coefficients, commencing from the final decomposition level. Therefore, the DWT coefficients equal the coefficients of the original signal.

D. *Architecture of Deep Recurrent Neural Networks (RNNs) for Effective Lossless Compression*

Using a series of vectors, recurrent architecture can propagate past information to the current unit (i.e., represented by hidden state vectors) through RNN operations. Recurrent neural networks (RNNs) have demonstrated exceptional performance in time-sequence data processing, such as recognizing speech and processing natural languages [20]. The fact that a sample and its predecessors usually have a strong correlation is an important feature of a time sequence. The probability of a particular state in the hidden Markov model, a model that is frequently used in language processing, depends only on its prior state.

Let Y = $[y_1, y_2, \cdot\cdot\cdot, y_t]$ represent the sequence of data, with t representing the state label. The data at the first state is represented by Y_1, and the data at the t state is represented by Y_t. One way to formulate the Markov assumption in (9).

$$P(y_t\ |y_1, \cdot\cdot\cdot, y_{t-1}) \ = \ P(y_t\ |y_{t-1}) \qquad (9)$$

where, the conditional probability is expressed by P (·). RNN and HMM are comparable in that they both rely on an earlier state for computation of the current state. Unlike traditional ANNs, the RNN processes sequential data in a circular manner, meaning that each data instance in the sequence will receive the same processing, with each state's outcome depending on the state before it. The parameter sharing is also represented by this circular processing. One common technique to limit the number of parameters in a DL scheme is parameter sharing. Nevertheless, assuming sequential data Y = $[y_1, y_2, \cdot\cdot\cdot, y_t]$ the hidden state r_t can be expressed in (10).

$$D_t \ = \ f_d(X_{dy}y_t \ + X_{dd}D_{t-1} \ + \ b_t) \qquad (10)$$

where, X_{dy} represents the weight matrix from the source data to the hidden state andX_{dd}, the current state to the subsequent state. The bias variable is b_t. The nonlinear function of activation is represented by f_d (·), and the hidden state at time step t is indicated by D_t.Equation (11) and the output calculation at state t are very similar.

$$z_t \ = f_z(X_{dz}D_t \ + b_z) \qquad (11)$$

where, X_{dy}represents the weight matrix connecting the output and hidden state. $f_Z(\cdot)$ is the nonlinear activation function, and by is the bias.

Since the hidden state (D_t) is computed via forward propagation using the previous state as a basis, it can be thought of as the RNN model's memory. Sequential data from earlier states are also taken into account in the interim. Unlike a traditional neural network, some parameters in such forward propagation—such as the three distinct weight matricesX_{dd}, X_{dy},, and X_{dz}, —are shared throughout all steps. By reducing the number of trainable parameters, the parameter-sharing scheme improves the efficiency of the entire computation. Fig. 3 depicts the architecture of deep RNN-LSTM is given.

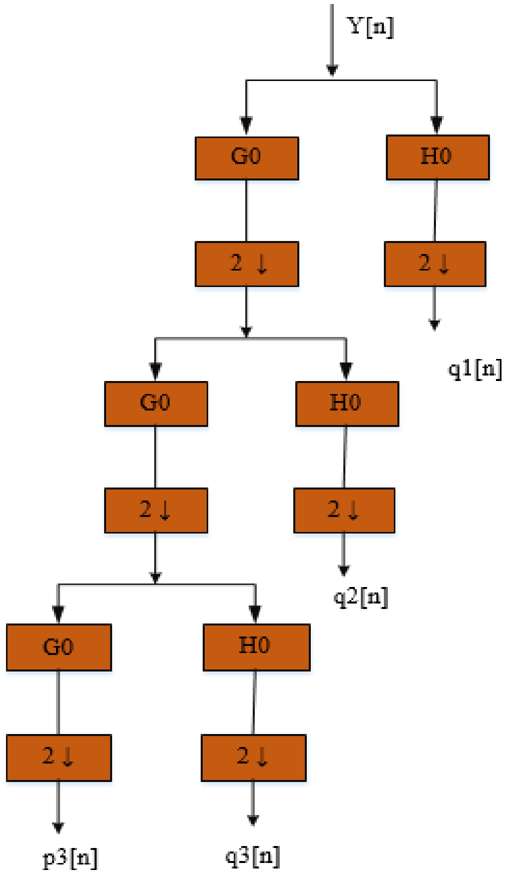

Fig. 2. Architecture of discrete wavelet transforms.

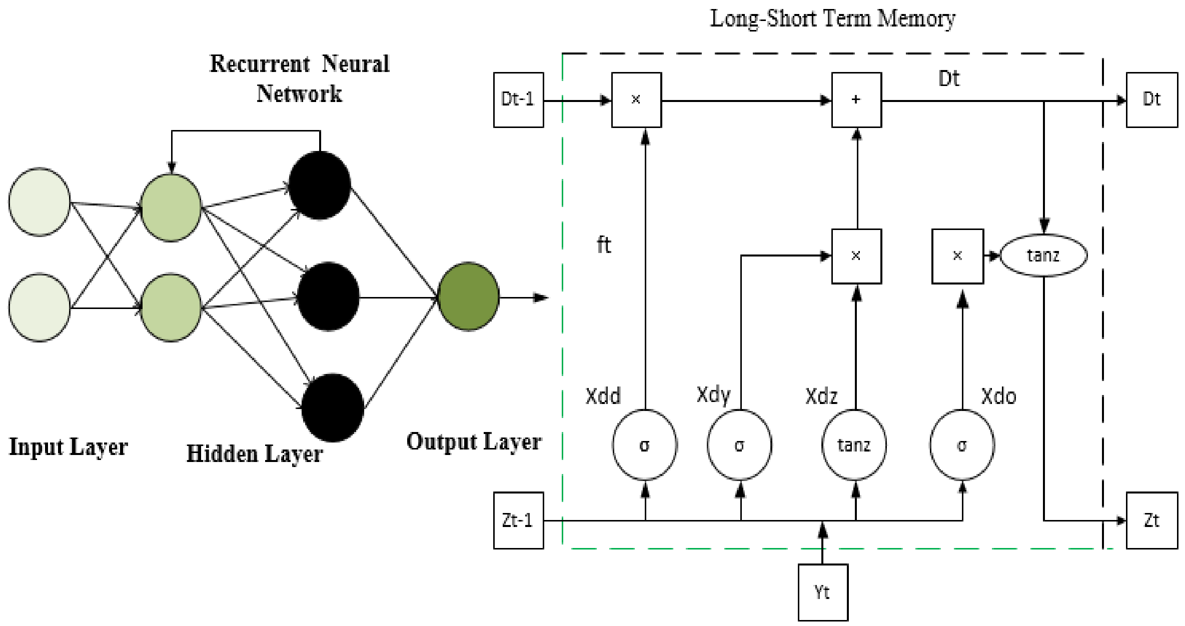

Fig. 3. Deep RNN–LSTM architecture.

LSTM was created using advanced recurrent neuron. Every recurrent neuron in an LSTM can be thought of as a single cell state [21]. LSTM uses the previous state as the input to the current state, just like the traditional RNN. To control the current neuron, the LSTM uses three gates: the forget gate, update gate, and output gate.

An LSTM network has the ability to recall and make connections between data gathered in the past and current. Three gates are coupled with LSTM: an input gate, a forget gate, and an output gate [22]. The input is denoted by D_t and D_{t-1}, denotes new and last state respectively, and the current and prior outputs by z_t and z_{t-1}.

Fig. 4 depicts the proposed DWT-RNN-LSTM Network model's overall workflow. The DWT-RNN-LSTM Network that has been proposed can efficiently compress hyper-spectral images with greater efficiency, and provide a more trustworthy for the lossless compression of images.

The following forms illustrate the LSTM input gate idea.

$$i_t = \sigma(\mathrm{X}_i \cdot [z_{t-1}, y_t] + b_i) \quad (12)$$

$$\widetilde{D}_t = \mathrm{tanz}(X_i \cdot [z_{t-1}, \mathrm{y}_t] + \mathrm{b}_i) \quad (13)$$

$$\mathrm{D}_{\,t} = f_t \mathrm{D}_{\,t-1} + i_t \widetilde{D}_t \quad (14)$$

where, Eq. (12) determines which piece of data should be added by passing z_{t-1} and y_t through a sigmoid layer. When z_{t-1} and y_t have travelled through the tanz layer, Eq. (13) is then used to get new information. In Eq. (14), the long-term storage data D_{t-1} into D_t and the present moment information,$\widetilde{D}_t$, are merged. X_i denotes a sigmoid output, while $\widetilde{D}_t$ stands for tanz output. Here, b_t stands for the LSTM input gate bias while X_i stands for weight matrices. The LSTM's forget gate then enables the dot product and sigmoid layer to selectively pass information. With a certain probability, the choice of whether to delete relevant data from an earlier cell is carried out. Eq. (15) is used to determine whether or not to retain relevant information from a preceding cell with a particular chance. X_f stands for weight matrix, b_f for offset, and σ for sigmoid function.

$$f_t = \sigma\,(X_f \cdot [z_{t-1}, y_t] + \mathrm{b}_f) \quad (15)$$

The output gate of the LSTM ascertains the necessary states for the subsequent Eq. (16) and Eq. (17) states provided by the z_{t-1} and y_t inputs. After obtaining the final output, the state decision vectors that send fresh data,D_t, via the tanz layer are multiply by it.

$$P_t = \sigma(X_o \cdot [Z_{t-1}, y_t] + b_o) \quad (16)$$

$$z_t = P_t \,\mathrm{tanz}(\mathrm{D}_{\,t}) \quad (17)$$

where, the weighted matrices X_o and the bias b_o, respectively.

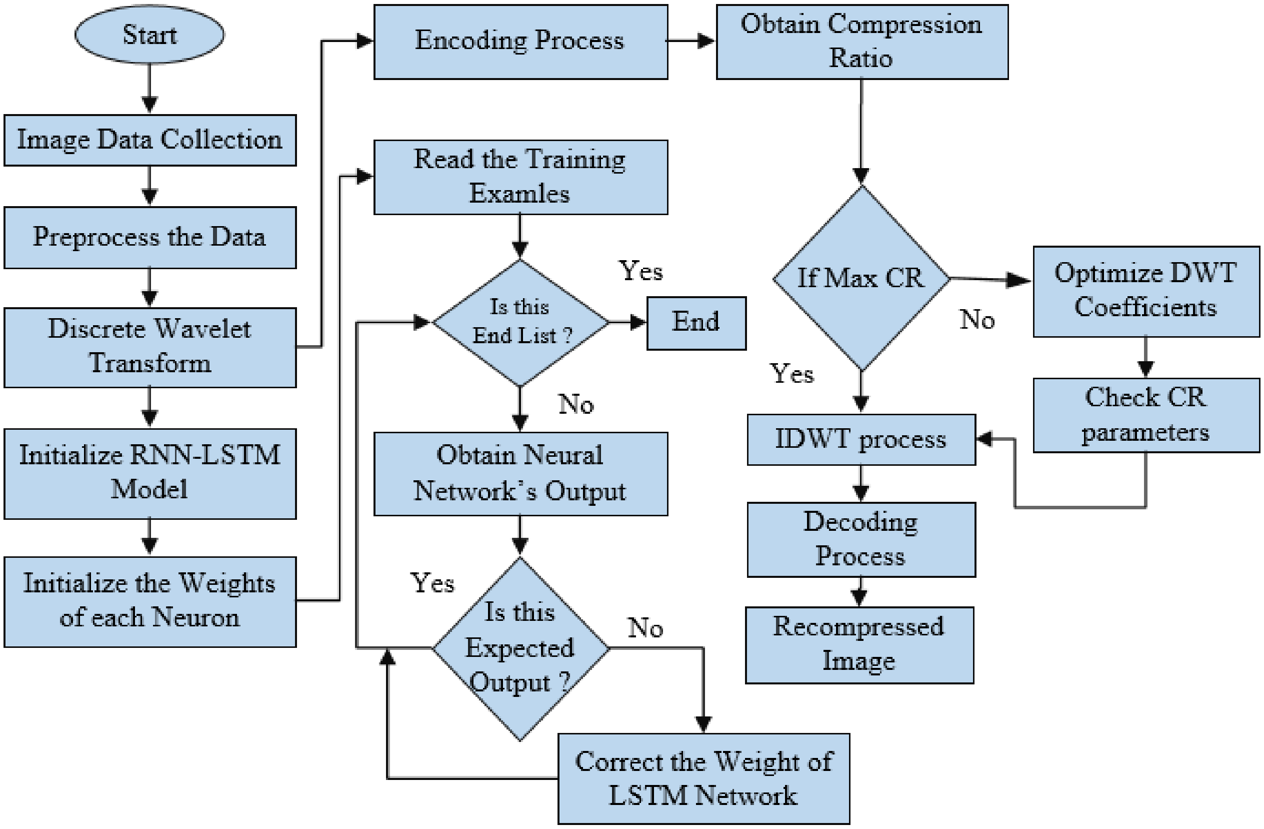
Start
Image Data Collection
Preprocess the Data
Discrete Wavelet Transform
Initialize RNN-LSTM Model
Initialize the Weights of each Neuron
Encoding Process
Obtain Compression Ratio
Read the Training Examles
Is this End List ?
Yes
End
No
Obtain Neural Network's Output
Yes
Is this Expected Output ?
No
Correct the Weight of LSTM Network
If Max CR
No
Yes
Optimize DWT Coefficients
Check CR parameters
IDWT process
Decoding Process
Recompressed Image

Fig. 4. Overall flow chart of DWT-RNN-LSTM method.

V. Results

The outcomes of the proposed methodology demonstrates how well it works to achieve optimal compression and consistent contrast enhancement for better data analysis in remote sensing applications. In order to ensure balanced information representation, histogram equalization is used as a pre-processing step, demonstrating its adaptability to multispectral data. By combining DWT with LSTM cells and deep recurrent neural network (DRNN), problems such as gradient vanishing or exploding are avoided and information fidelity is preserved while historical data is retained selectively. The methodology's success in capturing subtle features and managing hyper-spectral data efficiently is confirmed by the assessment of the impact of compression using pertinent metrics. The talk focuses on the potential for further developments, such as the investigation of optimization methods, incorporation of more machine learning algorithms, creation of models for adaptive compression, and expansion of applications to different remote sensing fields. On the Anaconda platform, the programming language of choice was Python. The following metric was used to assess the model's efficiency. The influence of compression on performance is carefully examined using appropriate metrics, and model parameters are changed depending on the compression model's unique requirements and the intrinsic properties of hyper-spectral data. This complete approach assures that the suggested technology not only accomplishes effective compression but also maintains information integrity, which is critical for remote sensing applications. Finally, the model's benefit is its ability to smoothly incorporate histogram equalization, multispectral transforms, DRNNs, and DWT, resulting in a comprehensive solution for advanced lossless compression in hyper-spectral image.

A. *Performance Evaluation*

Metrics for performance evaluation, like PSNR and MSE are essential for determining the quality of compressed or reconstructed images. Even though these metrics provide quantitative insights, subjective assessments are frequently added to obtain a complete picture quality assessment. A comparison is made between the suggested model and the performance of LSMA based compression, STW-WDR, and DPCM.

1) PSNR: PSNR for simple terms is a metric frequently used to assess the effectiveness with which an image has been compressed. When comparing the quality of a reconstructed or compressed hyperspectral image to the original, PSNR can be used to assess hyperspectral images, which are images taken in multiple bands across the electromagnetic spectrum.

The following Eq. (18) is used to determine the PSNR:

$$PSNR = 10.log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{18}$$

- The maximum pixel value that an image can have been referred to as MAX (255 for 8-bit images, for example).

- The average of the squared pixel-wise differences between the original and compressed images is termed as the Mean Squared Error, or MSE.

Since a higher PSNR value suggests less distortion or error in the compressed image, it typically denotes higher image quality. A higher PSNR is preferred in lossless compression since the objective is to reach high compression ratios without sacrificing the quality of the original image.

2) Mean Square Error: MSE is a statistic frequently used to express the average squared differences between matching pixels in two different images. MSE is frequently used in image processing and compression to assess how well a reconstructed or compressed image compares to the original.

The following Eq. (19) is the formula for mean squared error:

$$MSE = \frac{1}{n \times m} \sum_{p=1}^{n} \sum_{q=1}^{m} (I(p,q) - L(p,q))^2 \qquad (19)$$

- The intensity of the corresponding pixel in the original image is represented as I (p, q).
- In a compressed or reconstructed image, L (p, q) denotes the intensity of the corresponding pixel.

The squared difference between each pair of corresponding pixels is used to calculate the mean square error (MSE). This squared difference is then added up and divided by the total number of pixels (n × m). Better image fidelity is implied by a lower MSE value, which shows less variation between the original and reconstructed images. MSE, however, may not always correspond with human visual perception and does not directly account for perceptual differences. Because of this, when assessing image quality, it is frequently used in conjunction with other metrics and subjective evaluations.

The performance metrics of several image compression techniques, such as LSMA-based compression, STW-WDR, DPCM, and the suggested DWT-RNN, are compared in the Table I. The suggested DWT-RNN approach outperforms all other techniques in terms of PSNR, attaining a noticeably higher value of 45 dB. Additionally, it exhibits better Mean Squared Error (MSE) performance than the other methods, with the lowest value of 7.50%, indicating improved compression efficiency and image quality. These other methods include LSMA based compression, STW-WDR, and DPCM.

TABLE I. THE SUGGESTED METHOD'S PERFORMANCE METRICS ARE COMPARED TO THOSE OF EXISTING METHODS

Methods	PSNR (dB)	MSE (%)
LSMA based Compression [23]	33	20.57
STW-WDR [24]	35	18.02
DPCM [25]	30	17.09
Proposed DWT-RNN	45	7.50

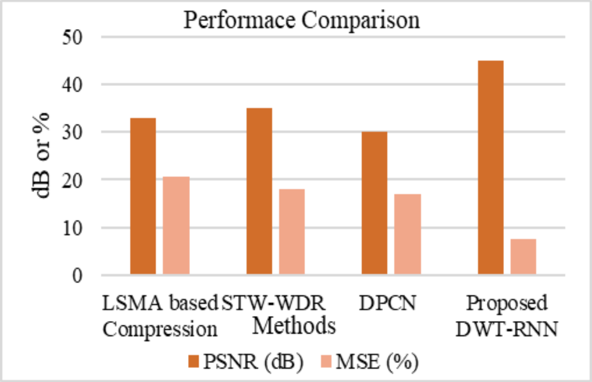

Fig. 5. Performance comparison with the existing methods.

Fig. 5 shows a graphical representation of the suggested performance metrics in comparison to the current methods. The proposed DWT-RNN-LSTM method demonstrates the highest PSNR Value when compared with existing methods.

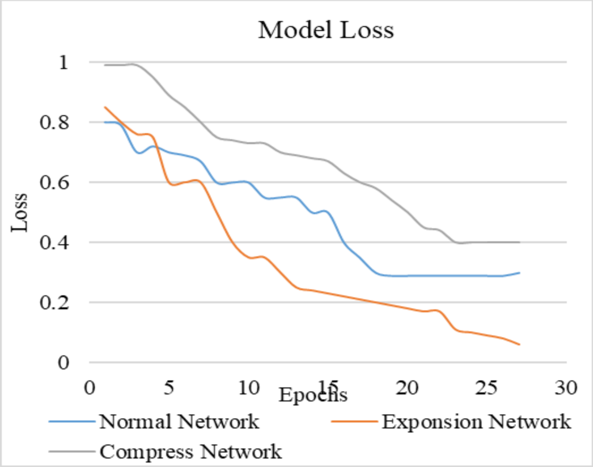

Fig. 6. Proposed DWT-RNN-LSTM method's loss is illustrated graphically.

The loss values against number of epochs are shown in Fig. 6. It shows the overall loss from the proposed DWT-RNN-LSTM Method's Loss is illustrated graphically.

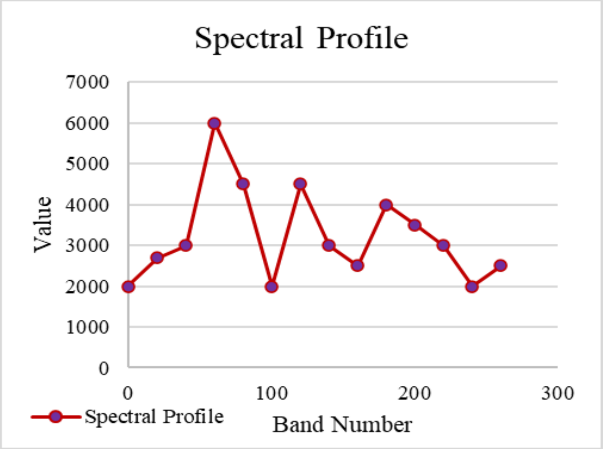

Fig. 7. Proposed DWT-RNN-LSTM method's spectral profile is illustrated graphically.

Fig. 7 depicts the graphical illustration of Spectral profile of the proposed model. The spectral profile is a critical component in advanced remote sensing image compression method because it allows for lossless compression in hyper-spectral imaging. The distribution of electromagnetic energy across different wavelengths, which captures the distinct signature of materials present in a scene, is referred to as the spectral profile. Optimizing compression efficiency requires combining deep recurrent neural networks (RNNs) with multispectral transforms.

TABLE II. PSNR OF DWT-RNN-LSTM METHOD IN EACH COMPRESSED RATION

Compression Ratio	PSNR (dB)
1	45
2	44
3	42
4	40
5	38
6	33
7	30
8	25

Table II represents the PSNR of DWT-RNN-LSTM method in each compressed RATION and it exhibits an effective lossless compression output.

Fig. 8 depicts the graphical illustration of PSNR of the proposed model. Higher PSNR values indicate better original information preservation. It provides a numerical measure of image fidelity by quantifying the ratio of the signal strength of maximum values to the noise introduced during compression.

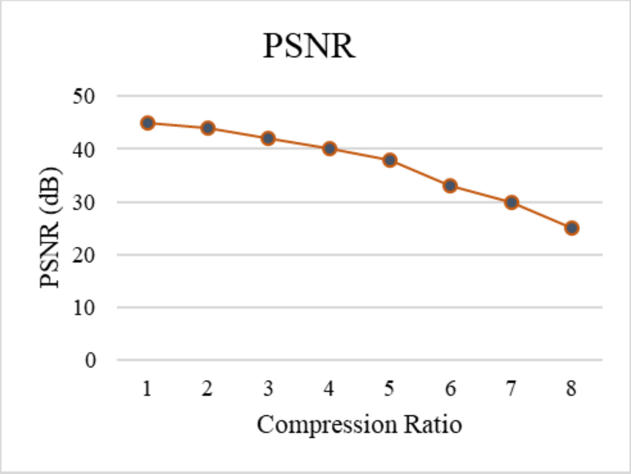

Fig. 8. Proposed DWT-RNN-LSTM method’s PSNR is illustrated graphically.

B. Discussion

The proposed approach to hyperspectral image compression shows notable improvements in attaining ideal compression and contrast enhancement for remote sensing applications by integrating DWT with LSTM cells and deep recurrent neural network. The approach's flexibility in handling multispectral data is demonstrated by the pre-processing step of histogram equalization, which guarantees balanced information representation. When DWT is combined with LSTM and DRNN, problems like gradient vanishing or exploding are successfully resolved, maintaining information fidelity and keeping some historical data. PSNR and MSE, are three performance evaluation metrics that show how much better the suggested DWT-RNN approach is than the state-of-the-art techniques like LSMA-based compression [23], STW-WDR [24], and DPCM [25]. In comparison to other methods, the higher PSNR value of 45 dB and lower MSE of 7.50% show better compression efficiency and superior image quality.

A graphic confirmation of the methodology's effectiveness can be seen. A performance comparison with current approaches is mentioned clearly, where the higher PSNR value of the suggested DWT-RNN is highlighted. The loss values are plotted against the number of epochs is shown graphically, which shows how stable and convergent the model was during training. The spectral profile of the suggested model highlights the significance of combining multispectral transforms and deep recurrent neural networks for the best compression in hyperspectral imaging. Lastly, Figure 8 shows the PSNR of the suggested model graphically, highlighting how well it can retain original data. Together with the quantitative metrics, these visual aids offer a thorough evaluation of the effectiveness of the suggested methodology for advanced hyperspectral image compression in remote sensing applications.

VI. CONCLUSION AND FUTURE SCOPE

In conclusion, this comprehensive and inventive hyper-spectral image compression methodology employs DRNN with long-short term memory cells, multispectral transforms, and histogram equalization for contrast enhancement. Problems like gradient vanishing and explosion are solved by incorporating the DWT, and spatial-frequency information capture is improved. The compression parameters are adjusted adaptively based on the needs of the model and the properties of the hyper-spectral data to ensure efficiency. Deep recurrent neural networks and multispectral transformations may limit real-time processing capabilities or necessitate high-performance computing infrastructure due to their probable requirement for large computational resources during both the training and compression phases. Future research directions include looking into more complex optimization strategies, incorporating more machine learning algorithms, developing adaptive compression models, investigating hardware acceleration, and expanding applications to different remote sensing domains, and designing intuitive user interfaces and visualization tools. This methodology establishes a solid foundation for future research into the compression of hyper-spectral images for various remote sensing applications.

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MR-FNC: A Fake News Classification Model to Mitigate Racism

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***Abstract*—One of the most challenging tasks while processing natural language text is to authenticate the correctness of the provided information particularly for classification of fake news. Fake news is a growing source of apprehension in recent times for hate speech as well. For instance, the followers of various beliefs face constant discrimination and receive negative perspectives directed at them. Fake news is one of the most prominent reasons for various kinds of racism and stands at par with individual, interpersonal, and structural racism types observed worldwide yet it does not get much importance and remains to be neglected. In this paper, to mitigate racism, we address the fake news regarding beliefs related to Islam as a case study. Though fake news remained to be a concerning factor since the beginning of Islam, a significant increase has been noticed in it for the last three years. Additionally, the accessibility of social media platforms and the growth in their use have helped to propagate misinformation, hate speech, and unfavorable views about Islam. Based on these deductions, this study intends to categorize such anti-Islamic content and misinformation found in Twitter posts. Several preprocessing and data enhancement steps were employed on retrieved data. Word2vec and GloVe were implemented to derive deep features while TF-IDF and BOW were applied to derive textual features from the data respectively. Finally, the classification phase was performed using four Machine-based predictive analysis (ML) algorithms Random Forest (RF), Naïve Bayes (NB), Logistic Regression (LR), Support Vector Machine (SVM), and a custom deep CNN. The results when compared with certain performance evaluation measures show that on average, ML-models perform better than the CNN for the utilized dataset.**

Keywords*—Machine learning; deep learning; fake news detection; social media

I. Introduction

One of the most challenging tasks while processing natural language text is to authenticate the correctness of the provided information particularly for classification of fake news. Fake news is a growing source of apprehension in recent times for hate speech as well. For instance, the followers of various beliefs face constant discrimination and receive negative perspectives directed at them. Fake news is one of the most prominent kinds of racism and stands at par with individual, interpersonal, and structural racism types observed worldwide yet it does not get much importance and remains to be neglected. In this paper, we address the fake news regarding beliefs related to Islam as a case study. Fake news is concerned with the type of racism done against Islam or Muslims which can be in the form of speech, text, news, attitude, behavior, or emotions. Any negative mention of Islam, Muslims, their mosques, rituals, religious practices, and holy books indicates the origin of fake news and recently United Nations Organization (UNO) has adopted a resolution to observe March 15 as international day to combat fake news [1]. Although it is one of the most prevalent forms of racism currently being noticed, no action has been made to confront or eradicate it. Web and social media are the major sources of spreading fake news-related content worldwide. As per Belgium's statement on fake news, political discussions and actions that were sanctioned addressing Muslim women's headscarves, the production of acceptable meat, and other Islamic traditions increased in 2017 [2]. Anti-Muslim acts have also increased significantly in China. As per a poll conducted in China during the year 2018, the acts of intolerance have been noticed against Muslims in terms of job opportunities, indoctrination availability, medical facilitation. They also face biasness in their social and electronic media representations [3]. According to a report distributed by 2019 in Europe, incidents like the Christchurch terrorist attack, Philip Manshaus' attempted attack on the Baerum mosque, and some physical assaults that took place in the United Kingdom post Christchurch incident are all the result of religious discrimination, hate speech, and derogatory social posts against the followers of Islam [4]. Furthermore, hate crime, social harassment, abusive behavior, and other Anti-Muslim activities have amplified over time in France [5], America [6] because of Donald Trump's statement regarding Anti-Islamic culture, Canada [7], Wisconsin [8], India during COVID-19 [9], and Israel [10]. Fake news is a major issue that is on the rise but has not been recognized on higher levels thus making it a matter of concern to figure it out and analyze its progress over the physical and electronic channels [40, [41]. Apart from this, the followers of Islam vary across different countries in terms of number which also impacts the level of fake news activities occurring in a particular region and there is no specific way to analyze it generically.

Some of the aspects that contribute to propagating fake news include lack of Islamic knowledge, a superficial and abstract understanding of its enactments, a non-acceptance behavior, extremist nature, and irresponsibility concerning other beliefs. A study done in USA during 1993 indicates that most people had negative ideas about Islam despite having little to no understanding of the religion. The balance of the population had positive impressions of Islam and knew something about it. This is because there is a deluge of inaccurate, unfriendly, and arsonist-related news about Islam and its followers on electronic channels. When a novice attempts to learn or research something, they only ever receive these inaccurate feedbacks [11]. Even while most communal channels have developed hand-made strategies for the brisk rectification of extreme content, there is still a long way to go in terms of automating this process. It is necessary to move away from the labored process of going through each article, tweet, or any electronic post, in favor of an automated system that can input a corpus of textual data, identify the content, and categorize it. The developments in the field of processing semantics language, machine-driven understanding of stuff, and layered models have assisted in the development of such systems that can orderly perform such tasks with utmost accuracy [12]. These tools are being widely utilized in the latest social media platforms and have provided great results till now.

In the proposed work, we contribute to propose a fake news classifier (FNC) model as follows: fake news data instances retrieved from Twitter is analyzed and classified using a variety of ML frameworks with the addition of a DL schema; the labeled tweet data is dispensed as an input to the constituted model in the form of single and multiple combination sets, and the model's operation is divided into various layers; it is then passed through the phase of preprocessing and features extraction based on deep and text features extraction techniques including Word2Vec and GloVe, BoW, and TF-IDF respectively; the extricated textual attributes are then given to several ML models LR, SVM and RF while the features derived from word embedding models are provided to a custom CNN for classification; finally, the results are evaluated based on several execution assessment metrics.

The rest of the paper is as follows: Section II provides a literature review of the techniques used by previous works for Islamophobic news classification and text analysis. Section III provides insights of the proposed work of this research study. All the experiments conducted along with their results and performance evaluations are listed in Section IV. Section V provides a discussion of results obtained and finally, Section VI concludes the proposed work.

II. Related Work

In recent years, there has been a rise in the quantity of study looking at different religious organizations in terms of their racial makeup, religion, gender, representation, and degree of equality. Numerous studies have been conducted on the topic of fake news because of the surge in hate speech, online publishing, and social media content that is directed towards Muslims and Islam worldwide [13]. However, a few studies have been conducted on the automatic detection of anti-Islamic content. A brief synopsis of these investigations is provided in the material below.

Mehmood et al. [14] performed the hate speech identification and isolation from 1290 tweets that were part of a publicly available twitter collection. Out of the 1290 tweets gathered, 566 are classified as unfavorable and 724 as positive. Preprocessing processes for the raw data include case folding, tokenization, removing superfluous words, cleaning, and breaking words rectification. 1D-CNN and other RNN variations are created and used to conduct feature ex-traction and categorization. 80% of the data is utilized for model training, while the remaining 20% is used for model testing. Several RNN and CNN combinations are used to get the findings. While using the CNN with Bi-LSTM, which is the most accurate method, the maximum accuracy of 90% is achieved. Chandra et al. [15] presented a tweet based CoronaBias dataset to do the analysis of social media data for Islamophobic content. Between the months of February and March 2020, CoronaBias included 410,990 tweets, and every single one of them had terms relating to Islam or Muslims. BERT and SVM are used to annotate the data. A total of 2000 good and hate tweets are retrieved for model training, and the PELT method is used to do temporal analysis on them. Positive matrix factorization, which increases the model's capabilities, is used for feature derivation. The results are studied, compared, and tracked using graphical representations and a few metrics, and it can be shown that the proposed BERT model provides the best accuracy results with a rate of over 85%, which is higher than the SVM's rate of 79%.

In this work [16], Khan et al. gathered twitter data for the first six months of 2020. The 17,228 tweets that were gathered were annotated by skilled humans after going through necessary pre-processing procedures. The experiments are carried out using deep and textual feature extraction methods. Additionally, ML and DL approaches are used to classify tweets into different polarity categories. Because of embedment of deep and text attributes, the SVM model offers an accuracy more than 95% on the validation data. Alraddadi et al. [17] categorized text utilizing sentiment and text analysis techniques. Arabic dataset obtained for the 3 months of 2021is based on news articles and publications from famous search engines. The Octoparsescraing program is used to assemble the relevant data into an Excel spreadsheet. The input data is subjected to pre-processing methods while for feature selection, n-grams and term frequency computation models are used. Resultant data is sent to multiple ML algorithms for feature creation and data categorization based on labels. Results are derived using the model while considering several performance monitoring standards after data is divided into a 70-30% division. For word-level, balanced, and non-balanced datasets, the TF-IDF and SVM combination yields successful results with accuracy above 97%. Vidgen et al. [18] examined data from social media to categorize the content that contains strong and mild Islamophobic hate content. Tweets more than 100 million are collected from Twitter for the entire year of 2017 and the first half of 2018. The final dataset comprises 1300 tweets after 4000 tweets from this data collection are picked as a training batch and manually annotated. Several features are generated using deep and text extraction methods which are then supplied to ML and DL models for categorization. DL model delivers the best outcomes and perform almost equally, with accuracy of 71.14%. The results are obtained for various data sets, and they are afterwards further evaluated using certain metrics. The authors [19] used AI methods to analyze the data from social channels. The data utilized is based on comments from various writers' and authors' personal blogs and is collected based on several keywords. The findings, which were generated with the use of various execution criteria, demonstrate that the accuracy of the RF and bagging classifiers is practically identical at 0.66%, and pre-processing did not increase the results any further.

The authors in [20] examined tweets about Islamophobia from the time when the Christchurch incident occurred in 2019. The study's data is based on 3100 deleted tweets from the time of mishap. Tokenization, stop word removal, and scraping are a few of the preparation and refining processes the data goes through. NB and SVM models are used in the classification procedure. The results are based on both the unbalanced set and the data labelled using the Valence Aware Dictionary and Sentiment Reasoner. Along with the two ML models already described, the synthetic minority oversampling method is employed to derive and compare results. In the work [21], the authors also examined tweets for the trace of Islamophobic material. They gathered 150,000 tweets from 2018 and professional annotators manually categorized them into polarity ratings. Before sending the data to the ML-models, pre-processing is performed. Both in terms of accuracy (98.1%) and processing time, the RR classifier outperforms the Bayesian classifier. Gonzalez-Pizarro et al. [22] used contrastive learning to study the hostile attitudes on political data acquired from Papasavva. 134,5 million political postings from June 2016 to November 2019 are included in the data. In addition to this data, a collection of 5,859, 439 pictures were also collected from Zannettou. The data is given ratings, and after going through a few pre-processing steps, TF-IDF is utilized to look for hate speech content. For the extraction of features, all photos with a cosine similarity index of at least 0.3 are chosen and compared with the textual data using several API’s. With precision up to 80%, the results show 69,000 antisemitic and 100,000 hate content from the entire data collection.

From the above discussion, it can be observed that some works have utilized embedding models, others have made use of n-grams for the derivation of useful data attributes. Also, there is a huge gap in Islamophobic content detection because to date only the above-mentioned studies have been conducted. Moreover, the results have been concluded based on either by using ML or DL models. Taking the lead from this, this study’s conducted work focuses on implementing the combination of all for a better comparison of each model’s performance on the currently utilized Islamophobic news data.

III. Proposed Methodology

The proposed research focuses on identifying and categorizing social media corpora that are associated with Islamophobia. The dataset of extreme and hateful tweets against Muslims and the Islamic faith was gathered from Twitter and other internet sources, pre-processed, cleaned, and subjected to several word embedding and n-gram algorithms, such as Word2Vec, Glove, TF-IDF, and BOW, for analysis. RF, SVM, LR, and a deep model CNN are some of the existing ML-algorithms that are used in the final step of data categorization. Accuracy, K-fold cross-validation, and F1-score are a few assessment metrics used to analyze the outcomes. Fig. 1 represents a detailed flow diagram of the proposed model.

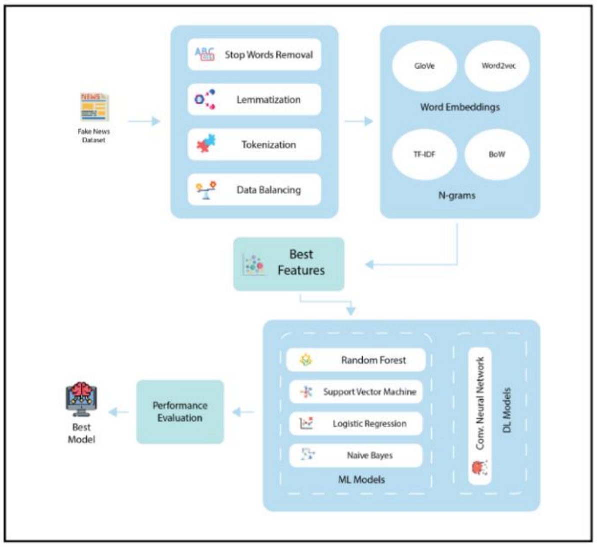

Fig. 1. Proposed framework.

A. Dataset

Tweet dataset exploited in the study is based on tweets and is not focused on a specific country to track the spread and effects of Islamophobia globally. Based on lexicons from Hate-base, some pre-defined hashtags were utilized for data retrieval during first six months of 2020 [23]. The data is scattered since it doesn't concentrate on user accounts, but it is nevertheless retrieved using an impartial technique. The 8438 English-language tweets in the study's dataset were pre-annotated by three annotators who are fluent in the language. The tweets were labelled into one of the three pre-defined categories namely Anti-Islamic, about Islam but having positive sentiment, and neither about Islam nor having any bad sentiments about Islam. The editors worked with data that was completely devoid of user and tweet identities. With considerable care, the annotators assigned the labels, and in cases of a tie, consensus casting ballots assignation was also employed. Table I provides an overview of data statistics.

B. Dataset Preprocessing and Balancing

Data preparation serves as the foundational stage for every classification work since it prepares, cleans, and removes ambiguities from the data [24]. Conversion of alphabets into smaller notations, end word rectification, hyperlink removal, removal of false full stops and half-sentences, tokenization and lemma generation are some of the preprocessing techniques used in this study. As a result of the utilized unbalanced data, created randomly using a variety of sources, the proposed model may not perform well [25]. To address this problem, the class with the greatest number of tweets is chosen, and those from the other two classes are replicated at random to keep the frequency of tweets across all classes under consideration equal. The experiments and findings derivation use the balanced data from this point forward. Following data balancing, the total number of tweets in each class is shown in Table II.

TABLE I. OVERVIEW OF DATASETS ATTRIBUTES

Attribute	Value	Attribute
Total tweets	8438	Total tweets
Tweets containing Islamophobic content	2485	Tweets containing Islamophobic content
Tweets about Islam but not Islamophobic	2398	Tweets about Islam but not Islamophobic
Tweets neither Islamophobic nor Islamic	3555	Tweets neither Islamophobic nor Islamic
Tweets language	English	Tweets language

TABLE II. TWEET COUNT FOR EACH TWEET CLASS

Label	Tweets
Islamophobic	3554
About Islam Not Islamophobic	3554
Neither Islamophobic nor About Islam	3555

The created vocabulary magnitude for the balanced data after pre-processing seems to be 17861 unigrams with the distribution of tweet-length set at 14 words each tweet. After pre-processing the data with eight words per tweet, the same magnitude drops to 16580 unigrams.

C. Feature Extraction

After preprocessing the data and balancing it, the next phase to be performed is feature extraction in which data is converted into vector attributes for the ML and DL models to interpret it. Two types of features are derived from dataset including word embedding based deep features and textual features which are described in next sections.

1) Word embedding: Word embedding is used to convert and represent textual data comprised of words into a vector and mathematical representation [26], [27]. Many models are available for this purpose, but in this study, we utilized the pre-trained GloVe from Stanford NLP and Wor2vec from Google news vectors. The GloVe is an unattended learning algorithm utilized for extracting word embeddings from the input data corpus based on the global word co-occurrence matrix. It is trained on global statistics of words included in a huge corpus compiled from online sources and when applied to any data, it directly obtains information about the words occurring frequently in that data and maps the words into vector spaces [28]. It has been widely utilized in text classification problems to derive features [29]– [31] and pass them on to classification models. It is based on the Log Bilinear (LBL) model that operates on the principle of weighted least squares [32] as Eq. (1) depicts.

$$d_a . d_b = logP\left(\frac{a}{b}\right) \tag{1}$$

Here, $d_a . d_b$ represent the weight density that any two data points carry within the corpus.Prepresents the co-occurrence probability of both the points. The complete working logic behind GloVe is represented in Eq. (2).

$$l = \sum_{a,b=1}^{n} f\left(G_{a,b}\right)\left(d_a^t d_b - \log G_{a,b}\right)^2 \tag{2}$$

where, l represents loss function, $f(G_{a,b})$ is the function that maps least-squares between both the points starting from 1 to onwards, $d_a^t d_b$ is the density of both the data points concerning time t, and $log\, G_{a,b}$ is the log of the function containing the square computation of data points. Word2vec is also a word embedding technique that works based on shallow neural networks and utilizes the skip-gram method to achieve this functionality [33]. It creates vectors of textual data included in the corpus based on the frequency of documents and their co-occurrence matrix. Eq. (3) demonstrates how Word2vec uses the skip-gram approach to do computation.

$$\frac{1}{T}\sum_{p=1}^{D}\sum_{-s\leq a\leq s, a\neq 0} log\, prob(word_{p+1}|word_t) \tag{3}$$

where, D is the corpus proportionality, p is the position of $word_t$ in data, $\log prob(word_{t+1}|word_t)$ indicates the logarithm of $word_t$ concerning incrementing positions and co-occurrences within the document [34]. In the proposed work also, the preprocessed data is delivered to both GloVe and Word2vec models, and the features derived by them are later given a customized CNN and the results are evaluated.

2) N-gram methods: N-grams are any sequence of word tokens in each data where n = 1 denotes unigram, n = 2 denotes bigram, and so on. An n-gram model can compute the probability of n-grams within a data corpus and provide a prediction. The use of such models becomes useful in text classification tasks where there is a need to count the number of specific words included in the vocabulary from the corpus [35]. Such a metric is the TF-IDF, which assesses how closely a word in a catalogue is connected to its mood or meaning. It determines the frequency of each relevant text and generates phrases with an inverse frequency of those that appear often throughout multiple articles [36]. TF-IDF analyzes document terms frequency in each document [37] represented in Eq. (4).

$$weight_{a,b} = freq_{a,b}^{t} x \log\left(\frac{N}{freq_a}\right) \tag{4}$$

where, $weight_{a,b}$ indicates the total weightage carried by the data two points, $freq_{a,b}^{t}$ calculates the appearance ratio of data point a in b, N shows the total documents count included in the corpus, $\log(\frac{N}{freq_a})$ computes the log of all included documents with the frequency of data point a. The textual material to be categorized can also be used by BOW to extract valuable properties. It operates using a specified vocabulary and uses that vocabulary to seek for the frequency of specific terms in the relevant material. The model only deals with whether familiar words occur in the document and has no concern about where they occur and it provides the histogram of given words within the data which can be easily given the classifiers [38]. BOW performs the creation of bags based on words based on Eq. (5).

$$doc_b = \sum_{a=1}^{N} weight_a^b\, xweight_a \tag{5}$$

where, doc_b indicates the document housing the targeted data point b. $weight_a^b$ shows the numerical weights of the repeating word for concerned feature point b included in the document. $weight_a$ indicates the weight of frequent word a that we are looking for in this scenario [39]. In the proposed work, both TF-IDF and BOW are used for the derivation of features from the preprocessed dataset. The extracted features from both these models are tested and classified using a set of four ML classifiers for classification.

D. Fake News Classification

After completing all the stages, the word embedding techniques' feature sets are fed into a DL algorithm called CNN, and feature sets derived from N-grams are directed to ML distributors. To perform the categorization against the derived attributes, the proposed work uses four ML-Classifiers: RF, SVM, LR, and NB well as a DL-based CNN that includes embedding, convolutional, max-pooling, and SoftMax layers.

IV. Experiments and Results

The suggested methodology uses word embedding and n-gram techniques to extract valuable characteristics from the input textual data based on Islamophobic news from social media, before performing classification using four ML algorithms and a CNN model. Word embedding features are first identified using a deep CNN, and then n-gram method-based features are sent to the four ML-algorithms for classification in a series of experiments based on word embedding, n-grams, ML, and DL model combinations. After balancing the dataset, each experiment is run, and the results are analyzed using a variety of performance analysis standards, such as recall, f1-score, 10-fold accuracy, and precision. In the first experiment, SVM is used to assess n-grams-based features. Table III mentions the results of SVM-TF-IDF and SVM-BOW with assessment metrics.

SVM is a ML classifier that is employed for the high-dimensional feature mapping process. Most frequently, it is used to categories and transforms data so that it may be used to sort records into their correct classifications. Using a renowned sklearn linear model package and n-gram based textual feature extraction techniques; we applied it to our categorical islamophobia data in the Python programming environment. 90% and 10% of the dataset are used, respectively, for training and testing the model. The number of folds is set to 10, and the maximum number of iterations is equal to 10000, for the k fold cross-validation procedure to test the model. As can be seen through Fig. 2, upon maintaining cross substantiation of 10-folds, it can be observed that the SVM in combination with the BOW technique obtains an accuracy of 97.3% as opposed to the 97.1% obtained by the SVM-TF-IDF.

In the following experiment, the RF classifier is given the same n-gram-based characteristics for the identification of Islamophobic material. Since the three used ML models are all the standard variety, we additionally used an ensemble model called Random Forest to further investigate the outcomes. Since Decision Tree is not an ensemble approach and produces almost identical hyperparameters as RF, we opted against using the most popular ML model. The library used to integrate the model into our environment is called sklearn ensemble, and the experiments employing this model are carried out using the Python programming language. 90% of the dataset is used to train the model, and 10% of the dataset is used to test it using k fold cross-validation with a fold size of 10 and 200 estimators.

The outcomes of the RF-TF-IDF and RF-BOW, with the identical assessment metrics, are shown in Table IV. Additionally, it can be noted that in this instance, when used in conjunction with the BOW model, the RF obtains an accuracy of 94.1% as opposed to the 91.4% obtained by the RF when utilizing TF-IDF when 10-fold cross-validation is maintained. As shown in Fig. 3, the RF and BOW combination also obtains greater f1-score, recall, and precision values than the RF-TF-IDF model.

TABLE III. Results of TF-IDF and BOW Features with SVM

PEM	**SVM – TFIDF**	**SVM - BoW**
10-Fold Accuracy	0.97	0.97
Precision	0.97	0.97
F1 Score	0.96	0.97
Recall	0.96	0.97

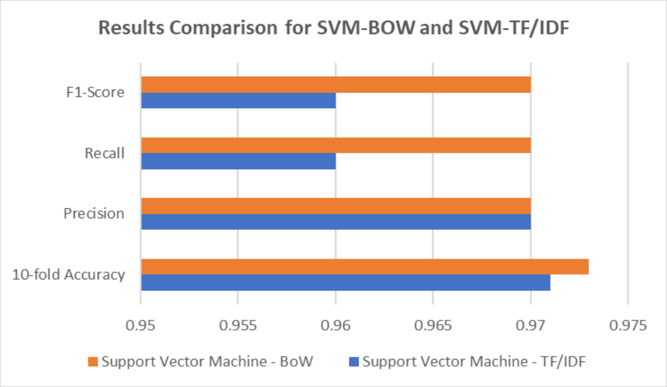

Fig. 2. Results comparison for SVM-BOW and SVM-TF / IDF.

TABLE IV. Results of TF-IDF and BOW Features with RF

PEM	**RF – TFIDF**	**RF -BoW**
10-Fold Accuracy	0.91	0.94
Precision	0.92	0.94
F1 Score	0.92	0.93
Recall	0.92	0.93

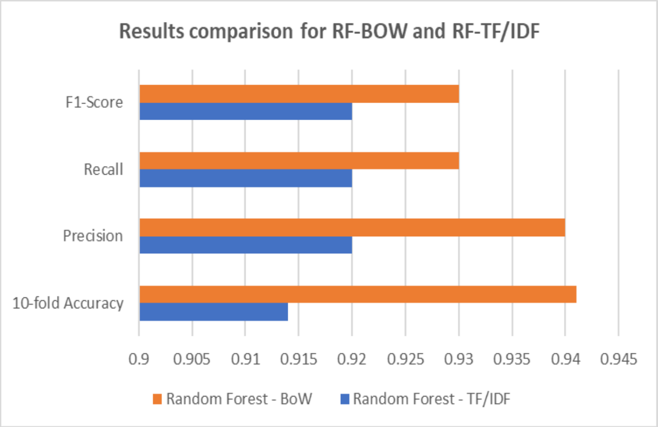

Fig. 3. Results comparison for RF-BOW and RF-TF / IDF.

TABLE V. RESULTS OF TF-IDF AND BOW FEATURES WITH LR

PEM	LR-TF-IDF	LR-BOW
10-Fold Accuracy	0.96	0.97
Precision	0.97	0.98
F1 Score	0.97	0.98
Recall	0.97	0.98

The experiment that follows uses an LR classifier to conduct classification based on the same n-gram characteristics as the ML models discussed before. Categorical data categorization in ML also employs LR algorithm. The finding of connections between probabilities and the outcome of the anticipated record is the first step in this model's major operation. We used this Python-based model to train and evaluate itself against our categorical data. 90/10 ratio is maintained for model's training and evaluation. Sklearn is the name of the library that was used to import this model into the experimental workspace. The outcomes of LR-TF-IDF and LR-BOW using the identical execution standards are shown in Table V

When TF-IDF linked model is maintained, BOW beats it by obtaining superior accuracy of 97.3 percent as opposed to 96.6 percent for the latter when coupled with an ML-classifier, in this instance LR. In addition, as shown in Fig. 4, LR-BOW outperforms LR-TF-IDF in all other performance metrics.

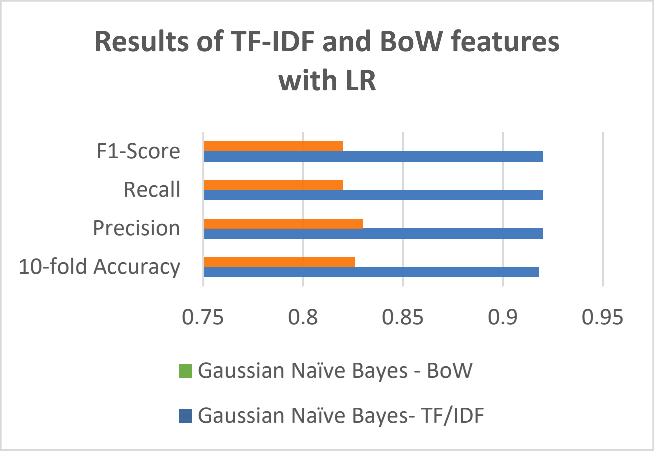

Fig. 4. Results comparison of TF-IDF and BOW with LR.

The GNB is used to classify with the features as an input, like in prior experiments, in this last experiment while utilizing an ML-classifier. Through its several iterations, which treat each input as an independent variable and forecast its likelihood, it aids in the rapid categorization of data. This technique is implemented in our codebase using the sklearn naive bayes package. For training and testing, the algorithm's Gaussian variant is employed, with data splits of 90% and 10%, respectively. The GNB-TF-IDF and GNB-BoW findings are displayed in Table VI.

When 10-fold cross-validation is maintained, TF-IDF outperforms its counterpart in this instance and obtains an accuracy of 91.8 percent as opposed to the 82.6 percent attained by the BOW-based model. In comparison to GNB-BOW, GNB-TF-IDF also outperforms it in all other performance metrics, as shown in Fig. 5.

The features retrieved by the word embedding models GloVe and Word2vec are further evaluated using a bespoke CNN after the implementation of four ML models with derived n-gram features. This model, which is a kind of deep neural networks, is primarily utilized for the accurate and quick categorization of vectorial data. The same data split utilized by ML algorithms is used to train and test this model when it is integrated into our software. The CNN is first trained and tested using Word2vec features with a batch size of 10 for model training and 32 epochs for testing. The number of epochs is kept at 5, and the batch size is kept at 32 for the k-fold cross-validation. Fig. 6 shows the training and validation loss for CNN using Word2vec.

TABLE VI. RESULTS OF TF-IDF AND BOW FEATURES WITH GNB

PEM	GNB-TF-IDF	GNB-BOW
10-Fold Accuracy	0.91	0.82
Precision	0.92	0.83
F1 Score	0.92	0.82
Recall	0.92	0.82

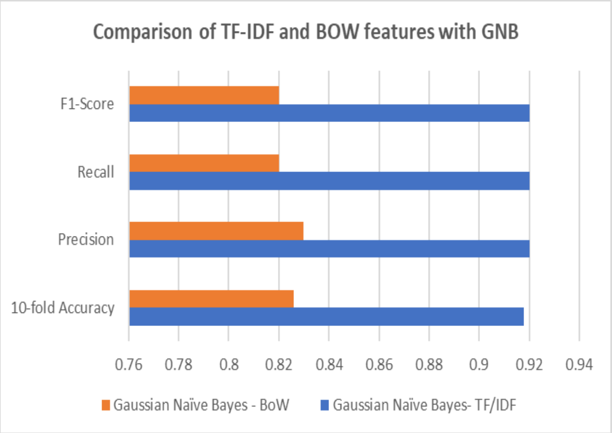

Fig. 5. Results comparison of TF-IDF and BOW with GNB.

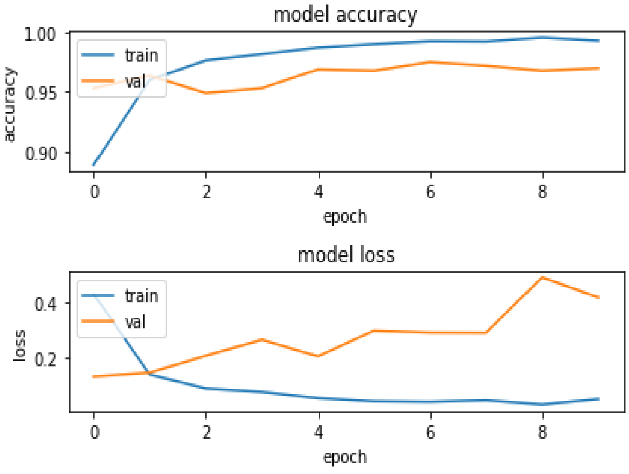

Fig. 6. Training and validation loss for CNN using Word2Vec.

Fig. 7 shows the training and validation loss for CNN using GloVe.

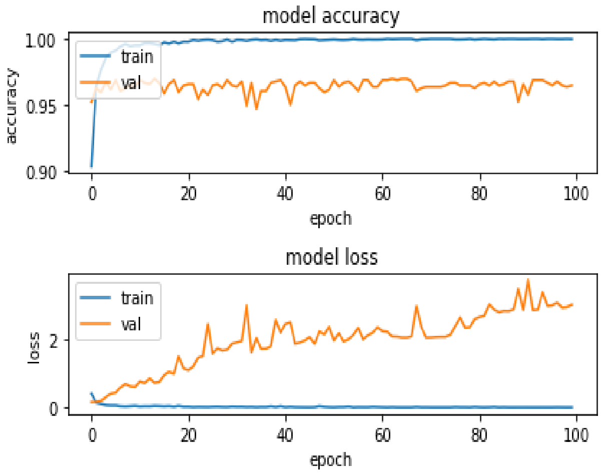

Fig. 7. Training and validation loss for CNN using GloVe.

Results for both embedding models with CNN are displayed in Table VII based on previously applied performance metrics.

TABLE VII. RESULTS OF WORD2VEC AND GLOVE FEATURES WITH CNN

PEM	CNN-Word2Vec	GNB-GloVe
10-Fold Accuracy	0.96	0.96
Precision	0.97	0.96
F1 Score	0.97	0.96
Recall	0.97	0.96

As observed in Fig. 3, Fig. 4, and Table VIII, CNN works a little bit better with Word2vec than GloVe because it obtains a better 10-fold accuracy and retains a higher evaluation rate. Table VIII gives a summary of all the experiments that were done above and gives a more comprehensive perspective of all the outcomes that were inferred.

TABLE VIII. RESULTS OF ML AND DL-MODELS WITH CORRESPONDING WORD EMBEDDINGS AND N-GRAMS

PEM	SVM-TFIDF	SVM-BOW	RF-TFIDF	RF - BOW	LR-TFIDF	LR-BOW	GNB-TFIDF	GNB-BOW	CNN-Word2vec	CNN-Glove
10-Fold Accuracy	0.97	0.97	0.91	0.94	0.96	0.97	0.91	0.82	0.96	0.96
Precision	0.97	0.97	0.92	0.94	0.97	0.98	0.92	0.83	0.97	0.96
F1 Score	0.96	0.97	0.92	0.93	0.97	0.98	0.92	0.82	0.97	0.96
Recall	0.96	0.97	0.92	0.93	0.97	0.98	0.92	0.82	0.97	0.96

V. DISCUSSION ON RESULTS

The findings of each experiment carried out for the planned study are covered in detail in the preceding section. It is clear from the trials on the characteristics that the n-gram models TF-IDF and BOW were able to extract using four ML-models that BOW outperforms TF-IDF in these scenarios. BOW outperformed its rival in terms of accuracy and other performance metrics when it was categorized using SVM, RF, and LR. Only when used in conjunction with GNB models did TF-IDF perform better. This demonstrates why it is preferable to use BOW-based features for the planned task.

The model also produced respectable results when Word2vec and GloVe word embedding features were classified using a custom CNN. The CNN-Word2vec model emerged as the superior one of the two because, as seen in Fig. 8, it performed better across the board.

The performance comparisons for the independently developed ML and DL models with n-gram and word embedding schemas are covered in the section above. However, this study demonstrates that ML-models typically outperform CNN in terms of categorization of the Islamophobic data utilized for this experiment. This shows that both SVM and LR outperform CNN at their maximal performance levels. Using both ML models stated, an average accuracy of 97 percent is attained, which is much higher than the 96.4 percent achieved by CNN.

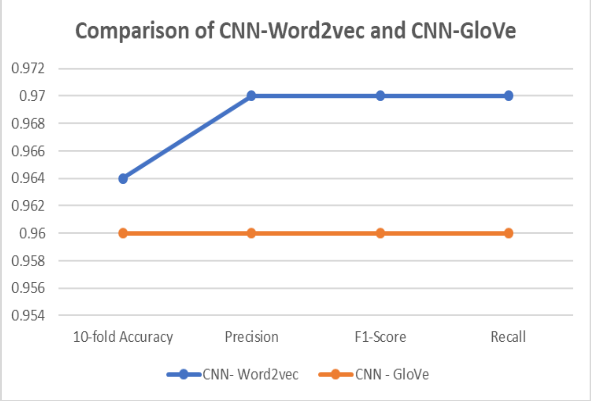

Fig. 8. Performance comparison of Word2vec and GloVe with CNN.

While the results of proposed work are quite encouraging, its performance is highly dependent on the characteristics of the data that can be further investigated in the future research work.

VI. CONCLUSION

It is alarming to see how hateful, exaggerated, extremist, and misunderstood misinformation about fake news and its impact on society is spreading on social media. Such material is accessible to a global audience, and as a result, various communities may be the target of harsh measures. The suggested project focuses on classifying such fake news content using data from Twitter. It uses several data cleaning and improvement procedures to refine the data. The implementation of Word2vec, GloVe, TF-IDF, and BOW word embedding, and n-grams methods follows to extract key characteristics from the data. Finally, four ML algorithms and a CNN created by the customer are used to classify the data. On average, the ML models outperform CNN and produce superior outcomes. The assessment of DL algorithms on this data might be done in the future using more DL algorithms like LSTM and RNN. Bert is the most recent DL feature extraction model based on a transformer that is becoming increasingly prominent in the field of sentiment analysis on textual data. While the results of proposed work are quite encouraging, its performance is highly dependent on the characteristics of the data that can be further investigated in the future research work.

Acknowledgment

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i-Tech: Empowering Educators to Bring Experimental Learning to Classrooms

A 360° Content Creation Tool

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***Abstract*—The integration of technology in education has gained significant attention, with Virtual Reality (VR), Augmented Reality (AR), and 360° VR emerging as transformative tools for enhancing student learning experiences. Despite their potential benefits, these immersive technologies have not achieved widespread adoption in education. Educators face numerous challenges in finding suitable 360° content for their courses and integrating complex content creation tools. Creating educational 360° content often involves hiring programmers or mastering intricate programming techniques, which can be time-consuming and daunting. Educators also struggle with finding platforms to host, edit, segment video content according to topics, and add subtitles and translations to their 360° videos. To address these challenges, this paper presents the implementation and evaluation of a user-friendly prototype tool with a step-by-step graphical user interface. This high-fidelity prototype assists educators in uploading 360° content, segmenting it into chapters or topics, incorporating questions or requirements within video segments, adding subtitles and translations, and facilitating content sharing among educators. This design aims to assist teachers in publishing their 360° content while reducing the complex VR programming for them. It enables them to integrate immersive learning in their classrooms with ease. The final goal is to promote greater adoption of 360° VR content in education and enhance learning outcomes.**

Keywords*—Virtual reality; 360° video; user behavior analysis; content delivery; immersive media; education; technology in education; instructional design; human-computer interaction

I. Introduction

Now-a-days, video content is employed in various forms to enhance the learning experience. As the barriers to accessing 360° video technology diminish, it has become increasingly effortless to engage with 360° content. In contrast to traditional media, 360° media offers a fully immersive and interactive simulated environment, providing students with a unique experiential perspective. Furthermore, this immersive approach helps minimize or even eliminate distractions that students may encounter.

While the use of 360° technology in education is gaining momentum, there is still ample room for improvement in this domain. The complexity involved in creating, processing, and disseminating 360° educational content, and making it accessible and beneficial for public consumption, contributes to this ongoing need for refinement. Undoubtedly, the integration of 360° technology in education presents educators with numerous challenges that may deter them from fully embracing this otherwise valuable tool. These challenges encompass both pedagogical and didactical aspects, such as effectively planning and designing virtual classrooms. Additionally, educators encounter various technical hurdles that impede the widespread adoption of 360° technology. These technical challenges include: (1) locating reliable resources that provide guidance on creating and publishing 360° media, (2) navigating the intricacies of these tools, particularly for novice computer users, (3) grappling with the time-consuming and labor-intensive process of designing and publishing content using multiple tools and frameworks, (4) addressing issues pertaining to subpar sound or image quality in the published media, (5) limited access to appropriate hardware and devices for capturing and viewing 360° content, and (6) insufficient bandwidth and network infrastructure to stream high-quality 360° videos in educational settings. (7) Moreover, concerns about data privacy and security when using immersive technologies in educational settings further add to the challenges educators face in adopting and implementing 360° technology.

This paper presents a prototype tool called i-Tech that aims to enable educators to process and publish their 360° content and share it with their students in one place. The tool provides a user-friendly step-by-step graphical interface, assisting educators in uploading their 360° content, segmenting it into chapters, incorporating questions/requirements before video chunks, adding subtitles to the video content, and making their content available to other educators in the field. This work aims to increase educators' adoption of 360° VR content in education and improve learning outcomes. While i-Tech is currently in the prototype stage, its purpose is to demonstrate the potential of such a tool and its impact on educational practices.

II. Literature Review

The utilization of VR, 360°, and mixed reality content in the field of education is not a new domain; it has been extensively explored in various research studies using different methodologies. In this section, we will delve into the concepts and applications of 360° media, as well as the incorporation of virtual reality (VR) and augmented reality (AR) technologies in educational settings. Furthermore, we will examine the challenges encountered in the design and development of 360° technology and explore existing endeavors aimed at providing educators with tools to facilitate the creation and dissemination of their 360° content online.

A. Background on 360° Media

The demand for enhanced immersion in virtual simulated environments has spurred the advancement of immersive technologies, leading to the emergence of novel forms of virtual reality (VR), augmented reality (AR), and 360° technologies. These technologies have revolutionized training programs by providing learners with engaging experiences that utilize multiple senses, such as sight, hearing, and touch, thereby facilitating effective knowledge acquisition. Among these advancements, 360° video technology has emerged as a promising and cost-effective solution for creating interactive virtual reality applications with immersive capabilities.

360° videos also referred to as immersive or spherical videos are filmed using a specialized camera that captures a panoramic view spanning 360 degrees. These cameras feature lenses positioned either on the top to capture the entire surroundings or on multiple sides to capture a comprehensive view from top to bottom and left to right. The captured images are then stitched together to create a seamless and immersive video experience. In contrast to traditional videos, which are limited to the camera's focal point, 360° videos provide viewers with the ability to explore and observe everything within the camera's range, resulting in a fully immersive viewing experience.

360° videos can be obtained through two main approaches: capturing real-life landscapes or creating computer-generated panoramas using 3D computer graphics software tools such as Blender [16], [1]. In the first approach, a specialized camera captures the entire 360° view of a physical environment. This allows for an immersive representation of real-world locations and events. Alternatively, in the second approach, 360° computer-generated panoramas are generated using software tools like Blender. These panoramas are created using 3D modeling and rendering techniques, providing the flexibility to design and visualize virtual environments with complete control over the content and scenery. Both methods contribute to the production of captivating 360° videos that offer viewers a rich and immersive visual experience.

The popularity of the 360° video format surged in early 2015, primarily due to its integration with YouTube. YouTube introduced support for importing and viewing VR videos in March 2015, making it accessible to a wider audience. Following in YouTube's footsteps, Facebook also embraced 360° videos and launched support for this format in September of the same year. In March 2017, Facebook revealed that over one million 360° videos had been uploaded to its platform, highlighting the growing interest and engagement with this immersive video format. Additionally, Vimeo, a prominent video-sharing website, joined the trend and introduced support for 360° videos in March 2017, providing another platform for creators to showcase their immersive content. These developments have contributed to the widespread adoption and availability of 360° videos across various online platforms.

In a 360° video, viewers are no longer limited to a fixed frame; they have the freedom to control the camera angle and explore the entire environment. This interactive viewing experience allows viewers to watch the video from multiple perspectives, offering an active engagement rather than a passive observation limited to the director's point of view. To enjoy a 360° video, viewers can use various devices such as personal computers, smartphones, or dedicated head-mounted displays. On computers and touch screen devices, viewers can navigate within the video by using a mouse or touch gestures. Smartphones equipped with internal sensors like gyroscopes allow users to pan the video based on the orientation of their device. For a more immersive experience akin to virtual reality, viewers can use stereoscope-style enclosures like Google Cardboard or Samsung Gear VR. These enclosures hold the smartphone and incorporate lenses that enable viewers to view the 360° video in a more immersive and engaging manner, utilizing the phone's display rather than a dedicated display found in virtual reality headsets.

B. Benefits and Challenges of 360° Videos in Education

The following literature review provides a comprehensive overview of the use of 360° videos, virtual reality (VR), and augmented reality (AR) in education. It explores the existing research and empirical studies to understand the potential benefits, challenges, and implications of integrating these immersive technologies in educational settings. Several authors have made significant contributions to the field of 360° videos, virtual reality (VR), and augmented reality (AR) in education. Their works have shed light on the potential benefits and challenges of integrating these immersive technologies into educational settings. Some important works include "If and how do 360° videos fit into education settings? Results from a scoping review of empirical research" [2] which presents a comprehensive examination of the integration of 360° videos in educational settings. Through a scoping review of empirical research, the study explores the various ways in which 360° videos are utilized and their effectiveness in enhancing educational experiences. The findings reveal that 360° videos have the potential to enhance student engagement, information retention, and the overall effectiveness of the learning process. However, the review also highlights certain challenges such as motion sickness and the limited availability of specialized 360° videos for educational purposes.

This work, titled "The Potential of 360° Virtual Reality Videos and Real VR for Education—A Literature Review" by [3], explores the potential of 360° virtual reality videos and real VR in education. It examines existing research and highlights the benefits and applications of these immersive technologies in educational settings.

The authors of [4] conduct a comprehensive examination of the research conducted on 360° video and its applications within the realm of education. Their work offers valuable insights into a wide range of studies carried out in this area, shedding light on the diverse potential uses of 360° video technology in educational settings.

Authors of the paper "Educational 360° Videos in Virtual Reality: a Scoping Review of the Emerging Research" [5] offer a comprehensive overview of the current research landscape surrounding educational 360° videos in virtual reality. The paper delves into the effectiveness and impact of these videos in enhancing learning experiences while examining the associated benefits and challenges. With its valuable insights, the paper serves as an essential resource for educators, researchers, and practitioners seeking to integrate immersive technologies, such as 360° videos, into educational settings.

Collectively, these works contribute to our understanding of the potential benefits and challenges associated with the integration of 360° videos, VR, and AR in education, providing valuable insights and guidance for educators and researchers in this field.

C. 360° Videos Challenges

360° videos pose a range of challenges for developers and users alike. Developers face the primary challenge of complexity when producing high-quality 360° videos. This complexity arises from the need for specialized equipment like multi-camera rigs and intricate post-processing techniques, adding both intricacy and cost compared to traditional videos [6].

Another challenge developer’s encounter is the increased bandwidth and storage requirements of 360° videos. Due to the expanded field of view, these videos typically have larger file sizes, demanding higher bandwidth for streaming or downloading. Managing encoding and compression is crucial for developers to ensure optimal streaming and playback experiences while maintaining video quality and reducing file sizes [7].

Platform compatibility poses an additional challenge for developers. Ensuring seamless performance across various platforms, devices, and operating systems is demanding. Developers must account for different video codecs, players, and technical specifications to provide a consistent experience to users across diverse environments [8].

From a user's perspective, in addition to compatibility issues, internet speed, device limitations, and bandwidth constraints, one of the significant challenges of 360° videos is the hardware requirements. Enjoying a high-quality 360° video experience often demands specialized hardware like virtual reality (VR) headsets or powerful smartphones. This requirement may limit accessibility for users who lack the necessary equipment.

Motion sickness is another challenge users may encounter when engaging with 360° videos. The immersive nature of these videos and continuous camera movements can lead to discomfort or motion sickness, resulting in shorter engagement durations and potentially impacting the overall user experience [9].

Limited availability of diverse and high-quality 360° video content compared to traditional videos poses another challenge for users. Finding compelling 360° videos on preferred platforms can be difficult, hindering overall enjoyment of the medium [10].

Interacting with 360° videos presents a learning curve for users, especially those unfamiliar with the technology. Understanding navigation controls and effectively exploring the content may require time and patience to fully grasp [11].

Users may also have concerns regarding processing power and battery life [11]. Rendering and playing back 360° videos demand more processing power, potentially impacting device performance and battery life. This concern is particularly relevant for users utilizing battery-powered devices such as smartphones or VR headsets.

Despite these challenges, continuous technological advancements, improved production workflows, and the growing adoption of 360° video content can help mitigate these obstacles and provide a more seamless and accessible experience for both developers and users.

In addition to the aforementioned challenges, adopting 360° video technology in education is faced with the following challenges:

Pedagogical integration: It is essential to integrate 360° videos into the curriculum in a meaningful and pedagogically sound manner. Teachers need to identify the appropriate learning objectives and design activities that align with the content of the videos [12].

Assessment and evaluation: Assessing student learning and evaluating the effectiveness of 360° videos as an educational tool can be challenging. Traditional assessment methods may need to be adapted or augmented to incorporate the unique aspects of 360° video experiences, such as student interaction and exploration within the video environment [13].

Teacher training and support: Integrating 360° videos into the curriculum requires teachers to have the necessary skills and knowledge to effectively utilize this technology. Providing comprehensive training and ongoing support to educators is crucial to ensure they can maximize the educational benefits of 360° videos and incorporate them seamlessly into their teaching practices [14].

These challenges highlight the importance of addressing pedagogical considerations, developing appropriate assessment methods, and providing adequate training and support to teachers. By tackling these challenges, educational institutions can harness the full potential of 360° videos as a powerful educational tool for immersive and interactive learning experiences.

Therefore, the design aims to alleviate users' time and effort regarding technical challenges and streamline the process of creating VR classes. We also evaluated our prototype platform, aligned with Norman's usability goals concerning effectiveness, efficiency, learnability, memorability, error prevention, and user satisfaction. We aimed to gain a comprehensive understanding of the participants' experiences with our platform and identify areas for future software production improvement.

III. I-TECH DESIGN AND IMPLEMENTATION

A. Design of the Platform

Our design goal for i-Teach (Immersive Teaching Enabler And Content hosting) is guided by Norman's design principles [15]. The primary objective is to alleviate users' concerns regarding technical challenges and streamline the process of creating VR classes, thereby saving their time and effort. Our team consists of one investigator who collaborated closely with a recruited programmer to handle the implementation aspect. Additionally, we have two UX investigators dedicated to designing and evaluating the platform. Throughout an entire semester, we conduct weekly meetings to brainstorm, discuss, and refine the platform's design, ensuring it meets the needs of educators and enhances their immersive teaching experience.

Our prototype platform offers a streamlined procedure comprising five steps to facilitate the uploading, editing, and publishing of 360° videos. Fig. 1 provides a visual representation of these steps. The sequential process is as follows:

- Get started: Users initiate the process by accessing our platform and starting the video upload procedure.
- Choose the video: Users select the desired 360° video file from their local storage or designated location.
- Entitle the video: Users provide a title or description for the video, furnishing relevant information to enhance its visibility and searchability.
- Video segmentation: As needed, users can opt to segment or divide the video into smaller segments to facilitate easier processing and management.
- Upload the video: Users finalize the process by uploading the 360° video file to our platform, ensuring its availability for subsequent editing or publishing.

By following these user-friendly steps, our platform empowers users to efficiently manage and publish their 360° videos, providing them with a seamless experience.

The landing page of i-Tech offers users a convenient file upload feature, enabling them to effortlessly upload their 360° videos for processing. Once uploaded, users are guided to define both the number and the duration of segments, as visually demonstrated in Fig. 2. Upon completing this step, users can proceed by clicking the "Upload" button to initiate the processing of their video content. Once educators have uploaded their videos, they will need to allow some time for the platform to process the data. During this processing period, educators can access their platform accounts and utilize the available YouTube functions, as shown in Fig. 3. It is important to note that user registration is not currently supported in our initial platform version, but it will be incorporated in future updates. However, in the meantime, educators can take advantage of the platform's integration with YouTube, enabling them to publish their 360° videos directly on the YouTube website. This seamless integration allows students to freely access and views the videos with ease, as depicted in Fig. 4.

B. Tool Evaluation: A Usability Testing

The primary objective of this study is to enhance the learning experience of students through the utilization of 360° immersive educational videos. To achieve this goal, we have developed a comprehensive prototype platform that empowers educators to seamlessly upload, edit, and publish their own 360° videos. One of the key advantages of our platform is its user-friendly interface, which eliminates the need for programming skills. This accessibility feature significantly reduces the time and effort required for educators to create their own educational VR content, allowing them to focus more on delivering impactful learning experiences to their students.

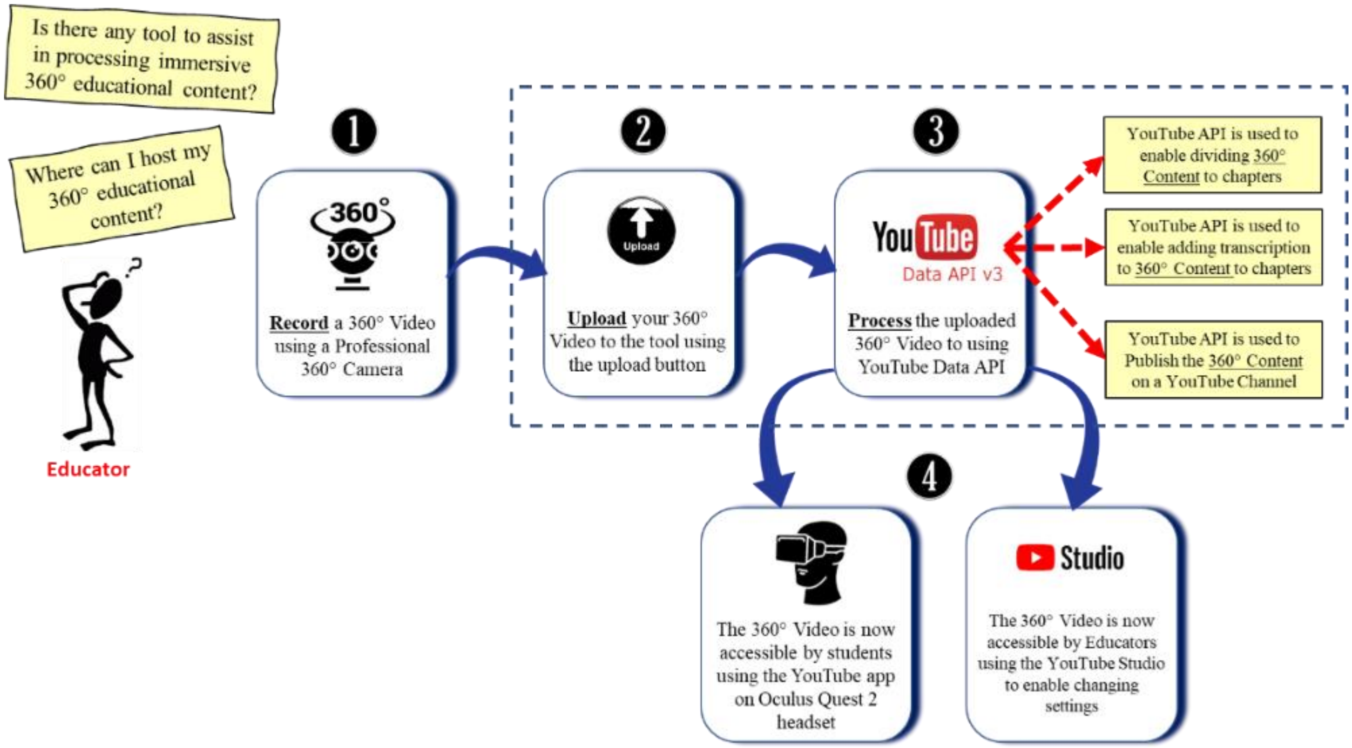
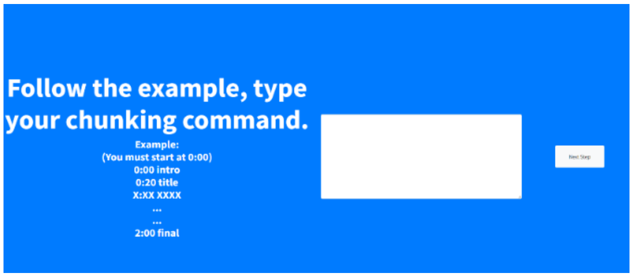

Is there any tool to assist in processing immersive 360° educational content?
Where can I host my 360° educational content?
Educator
1
Record a 360° Video using a Professional 360° Camera
2
Upload
Upload your 360° Video to the tool using the upload button
3
YouTube Data API v3
Process the uploaded 360° Video to using YouTube Data API
YouTube API is used to enable dividing 360° Content to chapters
YouTube API is used to enable adding transcription to 360° Content to chapters
YouTube API is used to Publish the 360° Content on a YouTube Channel
4
The 360° Video is now accessible by students using the YouTube app on Oculus Quest 2 headset
Studio
The 360° Video is now accessible by Educators using the YouTube Studio to enable changing settings

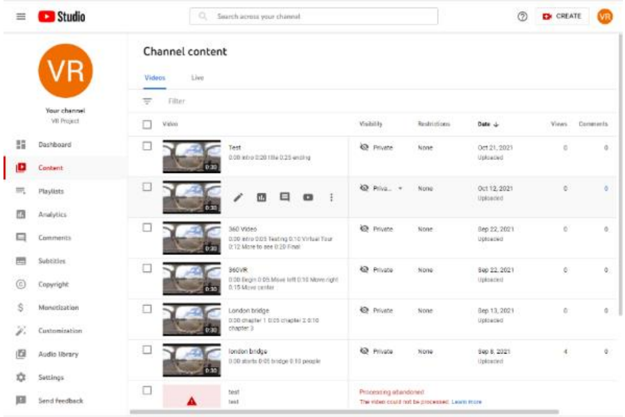
Fig. 1. Basic i-Tech structure and operation.



Follow the example, type your chunking command.

Example:
(You must start at 0:00)
0:00 intro
0:20 title
X:XX XXXX
...
...
2:00 final

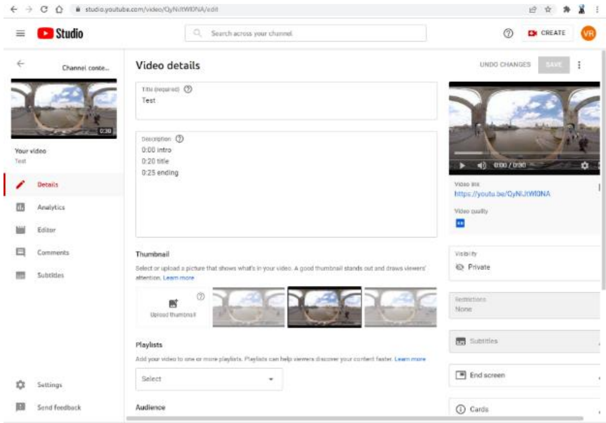
Fig. 2. Video segmentation facility i-Tech.



Channel content

Video	Visibility	Restrictions	Date ↓	Views	Comments
Test 0:00 intro 0:20 title 0:25 ending	Private	None	Oct 21, 2021 Uploaded	0	0
	Priva...	None	Oct 12, 2021 Uploaded	0	0
360 Video 0:00 intro 0:05 Testing 0:10 Virtual Tour 0:12 More to see 0:20 Final	Private	None	Sep 22, 2021 Uploaded	0	0
360VR 0:00 Begin 0:05 Move left 0:10 Move right 0:15 Move center	Private	None	Sep 22, 2021 Uploaded	0	0
London bridge 0:00 chapter 1 0:05 chapter 2 0:10 chapter 3	Private	None	Sep 13, 2021 Uploaded	0	0
london bridge 0:00 starts 0:05 bridge 0:10 people	Private	None	Sep 8, 2021 Uploaded	4	0
test test	Processing abandoned The video could not be processed. Learn more				

Fig. 3. Results in user's account.



studio.youtube.com/video/QyNiJtWI0NA/edit

Video details

Title (required)
Test

Description
0:00 intro
0:20 title
0:25 ending

Thumbnail
Select or upload a picture that shows what's in your video. A good thumbnail stands out and draws viewers' attention. Learn more

Playlists
Add your video to one or more playlists. Playlists can help viewers discover your content faster. Learn more

Video link
https://youtu.be/QyNiJtWI0NA

Video quality

Visibility
Private

Restrictions
None

Fig. 4. Published results.

TABLE I. THE EXPERIMENTS OF USABILITY TESTING

Participants' disciplines	Interview questions	Tasks
P1-information systems	Ease of use	Each professor was assigned a specific 360° video. They were required to upload, edit, and publish the video using our platform
P2-information systems	Ease and difficulty	
P3-Finance	Usefulness	
P4-Computer science and engineering	Suggestions	
P5-Geography	prior experience using or not using virtual reality	
P6-Communication	perceptions regarding the ease of generating VR content and integrating it into their teaching practice	

1) Evaluation participants: Nelson's (1993) recommended that as few as five users can effectively identify 85% of the usability issues associated with a particular technology [16]. Therefore, our study invited six full-time professors from a university located in the Midwest region of the United States to evaluate our high-fidelity prototype since our target users will be teachers. The participating professors represented diverse disciplines including information systems, computer science and engineering, finance, geography, and communication (see Table I). Prior to their participation, the study received approval from the Institutional Review Board (IRB), and the professors were invited to join the experiment after providing their informed consent by signing the consent form.

2) Evaluation tasks: To ensure the authenticity and naturalness of user interactions, the experiments were conducted in the participants' natural environments. This approach provided the advantage of observing the participants' natural process of interacting with our platform. The participants were initially instructed to perform various tasks using our platform, and their interactions were recorded using the Zoom share screen function. Following the task completion, the participants were then interviewed about their experiences, and these interviews were also recorded via Zoom. By conducting the experiments in this manner, we aimed to capture a comprehensive understanding of the participants' interactions and gather valuable insights from their firsthand experiences.

Prior to the experiment, each professor was assigned a specific 360° video and tasked with completing the upload, editing, and publishing tasks for that video using our platform (see Table I). The participants were required to go through each step of the platform, providing their insights and thought processes using the think-aloud method during the task execution. This approach allowed the investigator to gain a deeper understanding of how the participants performed the tasks and their decision-making processes.

Following the task completion, follow-up interviews were conducted with each participant. These interviews lasted approximately half an hour, during which the participants shared their experiences, thoughts, and feedback on the platform. Transcripts of the interviews were created to capture the details of the discussions.

The data collection process involved taking notes and recording videos of both the think-aloud sessions and the interviews. This comprehensive approach ensured that valuable information was captured and provided a rich dataset for further analysis and evaluation.

During the experiments, participants were prompted with think-aloud questions to elicit their thoughts and observations as they performed tasks on the platform. These questions included inquiries about their visual focus, the ease or difficulty of locating the next step, their understanding of video editing techniques, and any challenges encountered during the uploading process.

3) The interview sessions: Subsequent to the experiments, follow-up interviews were conducted to gather additional insights. The interview questions encompassed topics such as the participants' prior experience using virtual reality (VR) for teaching, their reasons for not utilizing VR if applicable, and their perceptions regarding the ease of generating VR content and integrating it into their teaching practice (see Table I).

In addition to these specific questions, we also incorporated usability-related inquiries aligned with Norman's usability goals. These goals emphasize the assessment of effectiveness, efficiency, learnability, memorability, error prevention, and user satisfaction. By addressing these usability dimensions, we aimed to gain a comprehensive understanding of the participants' experiences with our platform and identify areas for improvement. During the follow-up interviews, participants were asked a series of questions to assess their perception of the platform and its usability. Some of the key questions included (see Table I):

- Ease of use: Participants were asked to express their opinion on the ease or difficulty of using the platform to upload, edit, and publish the video. They were encouraged to provide reasoning for their response, highlighting specific features or aspects that contributed to their perception.

- Ease and difficulty: Participants were asked to identify the easiest and most challenging parts of the platform. This allowed them to pinpoint areas where they found the process intuitive and seamless, as well as areas that presented obstacles or required additional effort.

- Usefulness for teaching: Participants were queried about the usefulness of the platform for their teaching purposes. They were encouraged to elaborate on their response, discussing how the platform could enhance their teaching methods, engage students, or improve the learning experience.

- Suggestions for improvement: Participants were asked to provide feedback on areas of the platform that could be improved. This could include specific features, functionalities, or user interface elements that could enhance the user experience. Additionally, participants were invited to share their expectations for additional functions that they would like to see implemented in the platform.

By exploring these questions, we aimed to gather valuable insights from the participants to refine and enhance the platform, addressing their needs and preferences to create a more user-friendly and valuable tool for educational purposes.

4) Pilot study: To ensure the effectiveness of the tasks and interviews, a pilot test was conducted prior to the main study. The pilot test aimed to identify any confusing instructions or questions and to ensure the clarity and relevance of the provided information.

During the pilot test, a single participant was invited to complete the tasks and participate in an interview. The participant's feedback was valuable in identifying areas of confusion or ambiguity in the instructions and questions. Based on the participant's input, minor adjustments were made, such as reordering questions, rephrasing instructions, and removing redundant or similar questions.

It is important to note that the data collected from the pilot participant was not included in the final analysis since their participation was primarily intended to test the clarity and effectiveness of the instructions and questions, rather than to contribute valuable data to the study.

By conducting the pilot test and incorporating participant feedback, the study aimed to enhance the quality and reliability of the data collected from the main study, ensuring that the tasks and interviews provided meaningful and insightful information from the participants.

5) Data analysis: In this study, data were collected through multiple methods, including think-aloud Q&A, screen capture video analysis, and follow-up interviews. The collected data, including notes, videos, and interview transcripts, were analyzed using qualitative data analysis techniques.

The analysis process involved two main coding methods: open coding and axial coding. Open coding was initially conducted by the two researchers to identify preliminary concepts of interest. Printed documents, paper, markers, and a blackboard were used during discussions to facilitate the coding process. Due to the nature of the materials used, measuring inter-coder reliability was challenging.

After the open coding stage, axial coding was applied to identify and group themes in the data. The same two coders continued coding the data using this approach. The method of constant comparison was employed, wherein newly added transcripts were compared to previously identified concepts and categories that emerged throughout the analysis process (Corbin & Strauss, 2008; Merriam, 2009).

Throughout the analysis, the two researchers engaged in discussions to explore similarities and differences in the axial themes that emerged from the data. This iterative process allowed for a deeper understanding of the data and the development of meaningful interpretations.

By employing these qualitative data analysis methods, the study aimed to uncover insights and patterns within the collected data, facilitating a comprehensive understanding of the participants' experiences and perspectives related to the platform and its usage in education.

IV. I-TECH EVALUATION RESULTS

The designed platform was specifically created to provide professors from various disciplines with a user-friendly solution for uploading, editing, and publishing 360° videos to minimize their workload and technical challenges. To assess the effectiveness of the platform and gather feedback, a total of five professors from different disciplines were recruited as participants. These professors were invited to use the platform and subsequently interviewed to obtain their insights and opinions.

The analysis of the collected data focused on multiple perspectives, including task completion time and the occurrence of errors. By examining these factors, the study aimed to evaluate the platform's usability and efficiency in supporting professors with diverse backgrounds in utilizing 360° videos for educational purposes.

Through this analysis, the study sought to gain valuable insights into the platform's strengths and weaknesses, allowing for further improvements and refinements based on the feedback provided by the participating professors.

A. Task Time and Errors

The participants finished their tasks from three minutes to five minutes with an average of three minutes 25 seconds. All of them made no errors since they reported that the steps were simple and clear when they performed the tasks. However, three of them did have hesitations when trying to understand Step Three to segment the video into different chapters. After the investigator quickly asked them to view the example shown on the left of the page, they got the clue and finished the task without difficulties.

B. Themes from Think-aloud and Interviews

1) VR vs 360° videos: During the interviews, participants provided their perspectives on the differences between virtual reality (VR) design and 360° video when applied in their teaching scenarios. They unanimously expressed the belief that using 360° video for educational purposes is easier and more time-saving compared to VR design. Here are some of their responses:

Participant 1: "It is less complex. 3D programming needs lots of coding to do it. This one cuts the time for me to prepare for lessons."

Participant 2: "There is the use case (360° video). I worked with a camera. It was not that hard, just like put the camera on the tripod and shoot a video. This is very easy…I haven't worked with it (VR programming). But I think it involves some API. That study involves programming. So it's like a learning curve."

These statements highlight the participants' perception that working with 360° videos is less technically demanding and more accessible compared to VR design, which often involves programming and a steeper learning curve. They appreciate the simplicity and ease of use associated with capturing 360° videos using a camera, which allows them to focus more on the content creation and lesson preparation rather than technical intricacies.

The participants' consensus on the advantages of using 360° video suggests that it offers a convenient and efficient solution for incorporating immersive experiences into their teaching, saving time and reducing the complexity typically associated with VR design.

2) Ease of use: During the interviews, all participants expressed their unanimous agreement that the platform was easy to use, which aligns with one of the key usability goals of the project according to (Davis, 1989) [17]. Here are some of their responses:

Participant 3: "Just now, there were not a lot of things to do. From this perspective, I think it is easy...Every step is easy."

Participant 1: "I think it is quite easy and user-friendly to upload the video, and it is quite straightforward. The instruction is quite direct."

Participant 2: "It is easy. You just finish all the steps and then upload."

Participant 4: "It is not difficult. It is easy."

Participant 5: "It is easy to use."

Participant 6: "I think it's easy."

These responses indicate that all participants found the platform to be user-friendly and straightforward in its operations. They highlighted the ease of uploading videos and completing the required steps without encountering any significant challenges. The participants' overall consensus on the platform's ease of use validates the project's aim to create a user-friendly environment for educators to upload, edit, and publish 360° videos without facing technical complexities.

3) Usefulness: During the interviews, participants expressed their views on the usefulness of the platform for their current or future teaching. They recognized the potential value it could bring to their instructional practices. Here are some of their responses:

Participant 3: "I think it is a very good idea (to use this platform for her international business tours)."

Participant 1: "In the future, it might be quite useful for my courses. Students today like interaction, more visual attention to stay longer. It eliminates the explanation, and students could visualize it."

Participant 2: "It could be useful. It provides me with the way to upload and cut. So I do not have to worry about going to Youtube. I know (via) Youtube, or any platform, cutting it, you have to, the interface is just overwhelming. So I think this one is, the simpler, the better."

Participant 5: "Well, for my classes, I think it might be useful. Now I am thinking I can use it in the future."

These responses highlight the participants' recognition of the platform's potential usefulness in enhancing their teaching practices. They acknowledged the benefits of incorporating interactive and visually engaging content through 360° videos to improve student engagement and understanding. The convenience of uploading and editing videos directly on the platform was also highlighted as a significant advantage compared to other platforms that might have complex interfaces. Overall, the participants expressed positive attitudes toward the platform's usefulness, indicating their willingness to incorporate it into their teaching activities.

4) Integration of different functions: During the interviews, participants expressed their appreciation for the integrated functions of the platform, which alleviated the effort required to create 360° video classes. Here are some of their responses:

Participant 2: "I tried to use 360° video to teach before. So you have to go...Youtube allows some (to upload, edit, and publish), Facebook allows some others. There are some allowing photos, but you have to pay for videos. It is very confusing and useless... That's (the platform) easy and straightforward."

Participant 4: "In this platform, I do not need to learn some kind of new technology or combine different software together. Your platform provides all these required. This can reduce much time for customers."

These responses indicate that participants found the platform to be a comprehensive solution that eliminated the need to navigate multiple platforms or software tools to accomplish their desired tasks. The convenience and simplicity of having all the necessary functions integrated into one platform were highly appreciated. Participants highlighted the time-saving aspect of using the platform, as they no longer needed to spend excessive effort learning new technologies or managing various software tools. This further reinforced their positive perception of the platform's design and it’s potential to streamline their workflow in generating 360° video classes.

5) Expectations and improvements: During the interviews, participants shared their expectations for the future design of the platform, highlighting their needs in terms of feedback, display, and information accessibility. Here are some of their responses:

Participant 3: "Every step is so simple. I do not know how to improve."

Participant 1: "Overall, the platform is super easy for users. Maybe when you break down the video, you can immediately see which sections you can break down."

Participant 2: "The improvement is in the setting. For example, Step 1, like a big No. 1 to go next. A big number like the background. So you know where you are at in the process."

Participant 4: "To insert some part, for example, explanation voice or text function. If we have those that would be great."

These responses indicate that while participants found the current design of the platform to be easy and useful, they also expressed their desires for further enhancements. Participants highlighted the importance of clear visual cues and indicators, such as prominent numbers or markers, to provide a better understanding of the current step in the process. Additionally, they expressed a need for additional features like the ability to insert explanatory voiceovers or text, which would enhance the educational experience for both educators and students.

In summary, the design of our platform successfully provides educators with an easy-to-use and integrated solution that fulfills their basic needs for immersive educational videos. Through usability testing and participant feedback, we have confirmed that the platform is capable of assisting educators in achieving their educational goals. The participants' suggestions for future improvements provide valuable insights for enhancing the platform's functionality and usability even further.

V. Discussion and Future Work

Despite the increasing popularity of 360° videos and the potential they hold for enhancing educational experiences, there are certain limitations associated with the tools available for teachers to develop these videos and publish them. It is important to acknowledge these limitations in order to understand the current state of the technology and the areas that need further improvement.

One of the limitations lies in the complexity and accessibility of the tools used to create 360 videos. While there are software applications and platforms available that facilitate the creation process, they often require a certain level of technical expertise and can be daunting for educators without a background in video production or immersive technologies. Additionally, the cost of specialized equipment, such as multi-camera rigs or high-end cameras, can pose a barrier for schools and educators with limited resources.

It is important to highlight the significant advancements made in immersive technologies by devices such as the Facebook Quest 2 [18] and the Apple Vision Pro [19] Gear. The Facebook Quest 2 has gained popularity as an accessible and affordable virtual reality (VR) headset. It allows users to easily experience 360° videos and other VR content without the need for external sensors or a high-powered computer, thanks to its wireless and standalone design. On the other hand, the Apple Vision Pro Gear, although not yet released, is anticipated to be a device merging both virtual reality and augmented reality (AR) capabilities. By overlaying virtual objects onto the real world, it creates a mixed reality experience, enabling users to interact with digital content in their environment. These advancements in hardware technology are proving to be valuable for educators and students, as they make immersive experiences more readily accessible for educational purposes.

The metaverse [20] is a term used to describe a collective virtual shared space where people can interact with each other and digital content in real time. It combines elements of the physical and virtual worlds, creating an immersive and interconnected environment. In the metaverse, individuals can engage in various activities, such as socializing, working, learning, and exploring, using virtual reality (VR), augmented reality (AR), and other immersive technologies.

The concept of the metaverse has gained significant attention in recent years, fueled by advancements in technology and the growing popularity of VR and AR experiences. It represents a vision of a fully realized digital realm where individuals can transcend physical limitations and immerse themselves in limitless virtual experiences.

In the field of education, the metaverse holds great promise for transforming the way students learn and engage with educational content. By creating immersive and interactive virtual environments, the metaverse can offer new possibilities for experiential learning, simulation-based training, and collaborative problem-solving and global connections.

However, the full realization of the metaverse in education is still in its early stages. Technical challenges, such as creating seamless interoperability between different platforms and devices, ensuring data privacy and security, and developing user-friendly interfaces, need to be addressed. Furthermore, ethical considerations related to virtual experiences and the potential for exacerbating existing social inequalities should be carefully navigated.

Our current work aims to provide educators with a high-fidelity prototype that allows them to easily upload, edit, and publish their 360 videos for their immersive classes instead of using different sources to edit their videos and then find places to publish their videos, which brings lots of challenges to them. Our next step is to refine the prototype and make mature market-oriented software so that all educators can use it.

VI. Conclusions

In this paper, we introduce i-Tech, a novel tool designed to support educators in the creation and publication of their 360 video content. i-Tech offers a user-friendly and intuitive interface that empowers educators to leverage the immersive capabilities of 360 videos for educational purposes. Our main objective was to provide educators with practical solutions for easily uploading, editing, and publishing 360° videos to enhance the immersive learning experience of students. By utilizing video observation, think-aloud protocols, and interviews, we successfully integrated the necessary functionalities into our platform, enabling educators to create 360 class videos efficiently. While the availability of integrated 360° video platforms for educators is currently limited, the positive outcomes of our study offer valuable insights for future research in this field. The implications of our design can extend beyond educators and be applied to other user groups seeking to create 360° videos for various purposes.

However, it is important to acknowledge the limitations of our study. We conducted usability testing with a relatively small sample of seven professors from different disciplines. Despite the modest sample size, it aligns with Nelson's suggestion that even a small number of users can effectively identify a significant portion of usability issues in a technology. Additionally, our platform is currently in its initial version, focusing primarily on streamlining the process of cutting, uploading, and publishing 360° videos for educators.

In future studies, we plan to enhance the functionality of our platform to minimize technical challenges and provide a user-friendly experience for educators and other users. We believe that our study has made a valuable contribution to the understanding of integrated 360° video design, considering the limited existing research in this area. Our hope is that our findings will inspire designers and researchers to further explore this topic, leading to the development of innovative designs and applications that can benefit a broader range of users.

Acknowledgment

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Institutional Review Board Statement

The authors of this research study obtained the necessary approvals and/or waivers from the Institutional Review Board (IRB) at St Cloud State University for the project. The study was conducted in accordance with the ethical guidelines and regulations set forth by the IRB. Necessary measures were taken to ensure the protection of participants' rights, privacy, and confidentiality throughout the research process.

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A Lightweight Neural Network for Accurate Rice Panicle Detection and Counting in Field Conditions

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***Abstract*—Monitoring rice spikelet yield is crucial for ensuring food security, but manual observations are tedious and subjective. Deep learning approaches for automated counting often require high device resources, limiting their applicability on low-cost edge devices. This paper presents the Rice Lightweight Feature Detection Network (RLFDNet). RLFDNet designed for the field of computer vision, features a lightweight encoder and decoder, effectively decoding shallow and deep information within its neural network architecture. Innovative designs including dense feature pyramid network, reinforcement learning guidance, attention mechanisms, dynamic receptive field adjustment, and shape feature fusion enable outstanding performance in object detection and counting, even with low-resolution images. Across different elevations, ranging from 7m to 20m, RLFDNet demonstrates significantly superior accuracy and inference efficiency compared to other advanced object detection methods. With a parameter count of only 4.40 million, it achieves an impressive frame rate of 80.43 FPS on a GTX1080Ti GPU, meeting real-time application requirements on inexpensive devices. RLFDNet's exceptional performance is further highlighted by an MAE of 1.86 and an R² of 0.9461, along with an average precision of mAP@0.5 reaching 0.91. These results underscore RLFDNet's capability as a potent and reliable visual tool for agricultural practitioners, offering promising prospects for future research endeavors.**

Keywords*—Computer vision; deep learning; lightweight; neural network architecture; remote sensing

I. INTRODUCTION

Rice is a pivotal global crop, essential for food security, particularly for almost half of the world's population. Metrics like spikes per square meter and grain size profoundly influence cereal crop yield [1] [2]. However, accurately counting rice spikes encounters challenges due to outdoor environment complexities, including size variations, lighting conditions, and occlusion. Traditional monitoring methods hinge on manual observation [3], which is time-consuming and subjective, impacting rice quality and yield.

In recent decades, the rapid development of computer vision has made deep learning (DL) a key research field in artificial intelligence [4]. Similarly, deep learning has also been widely applied in agriculture, particularly in various agricultural information management practices [5] [6]. Many studies utilize machine learning for crop yield prediction by estimating the quantity of fruits, such as cotton [7], citrus fruits [8], sugar beets [9], and rice. In the realm of rice, various studies have been conducted: Xiong et al. [10] proposed a rice spike segmentation algorithm based on superpixel region generation, CNN, and superpixel optimization. This method effectively segments and recognizes complex rice spikes, but may involve unreasonable assumptions, such as simplification of rice spike shapes. Misra et al. [11] introduced SpikeSegNet for rice spike detection and counting, achieving an average accuracy of 95%. However, it overly relies on lighting conditions. Wang et al. [12] presented an algorithm utilizing three-dimensional point clouds for crop size estimation, particularly suited for spike counting in high-density scenarios, yet highly relies on high-quality sensor data. Shu et al. [13] proposed a rice spike detection method based on the SSD algorithm, with an average precision mAP of 38.1%. The model's accuracy still needs improvement.

Computer vision applications in agriculture, particularly in rice spike detection, have demonstrated significant potential. However, these models encounter critical issues such as low detection accuracy or lack of lightweight design, resulting in suboptimal user experiences and high entry barriers. Furthermore, due to variations in terrestrial environments, these methods are susceptible to significant errors.

Recognizing these challenges, researchers have turned to micro unmanned aerial vehicles (UAVs). Micro UAVs offer several advantages, including convenient platform setup, low operating and maintenance costs, small size, light weight, simple operation, high flexibility, and short operation cycles, making them an ideal choice for agricultural applications. Tri et al. [14] combined drones with deep learning to predict paddy field yields, marking the first use of drones for image collection and deep learning-based rice spike classification. Hayat et al. [15] proposed an unsupervised Bayesian learning-based segmentation algorithm for rice spike segments, achieving an average F1-score of 82.10%. However, they require significant computational resources and may not be suitable for real-time applications in resource-constrained environments. Reza et al. [16] introduced a method for rice yield estimation based on K-means clustering and segmentation of low-altitude UAV images. However, their method exhibits relatively low accuracy, with a relative error ranging from 6% to 33%, making it challenging to meet the requirements for automated detection of rice spike yield. In summary, further improving accuracy and efficiency is a natural and important research direction.

To address this challenge, the focus of this study is on achieving high accuracy and lightweight design in the model architecture, taking into account the deployment requirements of edge devices in the field of plant science. The proposed method for rice spike localization and counting is a deep learning-based approach named the Rice Lightweight Feature Detection Network (RLFDNet). RLFDNet utilizes the lightweight backbone CSPDarknet [17] and further incorporates a concise and efficient encoder-decoder module to decode features from both shallow and deep layers. Unlike existing methods, RLFDNet primarily aims to overcome the recognition challenges posed by small and dense targets. It offers several advantages: Firstly, it emphasizes higher spatial resolution to retain detailed information at each pixel position. Secondly, it focuses on extracting more discriminative high-level semantic information. Specifically, the model decoder maximizes the utilization of depth-encoded feature layers generated by the encoder to capture abstract information. By employing an adaptive strategy, RLFDNet effectively restores spatial resolution and merges feature layers from non-adjacent levels. Additionally, a channel attention mechanism is introduced to suppress irrelevant pixel information at critical positions, thus alleviating the difficulty of feature extraction in dense scenes. RLFDNet achieves a balance between accuracy and computational efficiency, making it suitable for real-world implementation on resource-constrained devices, unlike existing methods that often prioritize accuracy over computational efficiency.

To validate the universality of the model design, this study utilized the Diverse Rice Panicle Detection (DRPD) dataset [18], which was publicly released by Teng et al. [19]. It is noteworthy that this dataset comprises field rice spikes captured by micro UAVs at different altitudes (7m, 12m, and 20m) and subsequently cropped. Undoubtedly, varying the altitude during capture results in different target sizes and densities of rice spikes in the images, posing a significant challenge for object detection models. Fortunately, extensive experimental results demonstrate that RLFDNet's accuracy and inference efficiency are significantly superior to other advanced object detection methods, showcasing better robustness and adaptability. RLFDNet's parameter count is only 4.40 million, and it reports an outstanding frame rate of 80.43 FPS on the affordable GTX1080Ti GPU, making it sufficient for real-time applications when deployed on inexpensive devices. The efficiency comparison is illustrated in Fig. 1.

In summary, this study makes three main contributions:

- Innovatively introduces a more precise encoder-decoder module and cleverly designs an efficient neural network structure, significantly enhancing the integration capability of image features and effectively improving feature extraction performance.

- Proposes the lightweight RLFDNet model specifically designed for the localization and counting of field rice spikes. Its lightweight architecture allows for flexible deployment on low-end edge devices, providing a novel solution for automated monitoring of rice spikes.

- Through comprehensive comparisons with mainstream object detection models, demonstrates the outstanding performance of the RLFDNet model on rice spike datasets of different scales compared to state-of-the-art methods, highlighting its significant advantages in object detection tasks.

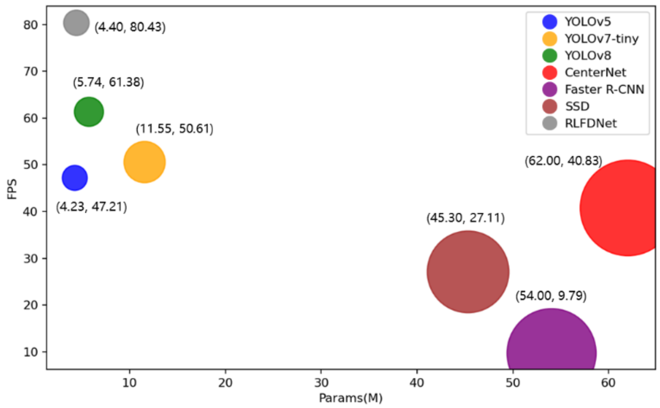

Fig. 1. Efficiency comparison of different models. Performed on a device with NVIDIA GTX1080Ti GPU (8G).

The layout of this paper is as follows:

In Section I (this section), the research background is introduced, and the problem statement is emphasized. Section II provides a detailed introduction and description of the proposed RLFDNet model. Section III conducts experiments and performs comprehensive comparative analyses with other models across various dimensions. Section IV delves into the factors influencing RLFDNet's performance and summarizes the model's innovative aspects. Section V concludes the study and outlines future research directions.

II. Materials and Methods

A. Datasets

This study is based on the publicly available dataset Diverse Rice Panicle Detection (DRPD) [19]. Aerial images of rice fields were captured at three different altitudes: GSD7m, GSD12m, and GSD20m. The images were cropped from the original aerial images, with each image having a size of 512×512 pixels. In total, 5,372 RGB sub-images were collected, annotated with 259,498 rice spikes exhibiting various morphological features. Details of the dataset are presented in Table I, where "Panicles per sub-image" indicates the number of spikes in each sub-image. The dataset includes four key growth stages: heading (1,903 sub-images), flowering (1,676 sub-images), early grain filling (1,235 sub-images), and middle grain filling (558 sub-images). It is noteworthy that, due to cropping by researchers and the high density of the aerial images, the difficulty varies across different altitudes. Rice spikes are larger and less dense at an altitude of 7m, presenting the lowest difficulty. In contrast, at an altitude of 20m, rice spikes are smaller, more densely distributed, and pose the greatest challenge. This requires the model to overcome challenges associated with low-resolution images and dense predictions. Additionally, factors such as different sizes, shapes, postures, occlusions, lighting conditions, and water reflections severely impact detection results. It is precisely because of these challenges that various methods were employed in the model design, carefully addressing these limitations to ensure the model's robustness and good overcome generalization performance. In this study, these challenges were successfully, leading to satisfactory experimental results, as demonstrated in the following sections.

TABLE I. DATASET DETAILS

GSD	Images	Labels	Panicles per sub-image
GSD_{7m}	3,810	106,878	27-30
GSD_{12m}	1,004	71,404	65-70
GSD_{20m}	558	81,216	140-150

B. Model Architecture

Taking into account the deployment requirements of edge devices in the field of plant science, the model architecture was designed with a focus on lightweight design. Effective design modifications were applied to the detection network structure, making it more comprehensive and detailed, particularly suitable for detecting rice spikes of varying sizes in the images. As shown in Fig. 2, the global architecture of the model consists of three main components: the Encoder for generating feature maps, the Decoder for feature parsing, and the Detector for visual output. The following sections will provide a detailed explanation of the design details and the rationale behind them.

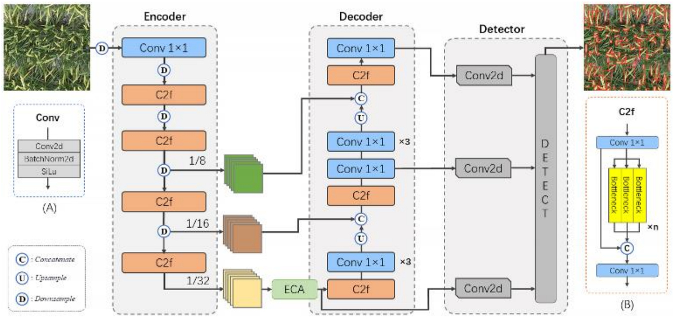

Fig. 2. The global architecture of the RLFDNet model.

1) Encoder: The role of the encoder is to map the input RGB image to feature maps. Given an input image $I \in R^{H \times W \times 3}$, RLFDNet employs the lightweight network CSPDarkNet [17] as the backbone for feature extraction. Down-sampling operations are performed using 2D convolution layers with a 3×3 kernel size and a stride of 2. CSPLayer [20] is inserted at different stages for feature extraction, combined with the C2f module [21] to generate feature maps at different stages. Through these operations, the input image undergoes 32 times downsampling, resulting in feature maps with channel numbers of 64, 128, and 256, representing 1/8, 1/16, and 1/32 of the original image, respectively. These feature maps carry richer gradient information and are utilized in the decoder.

In the final stage of the encoder, the Efficient Channel Attention (ECA) mechanism is applied. It compresses spatial information through global average pooling, learns channel attention information through a 1×1 convolution layer, and combines the channel attention information with the original input feature map. This approach avoids dimension reduction, effectively captures cross-channel interactions, and requires only a small number of parameters for excellent results. In summary, this encoder contributes to improving object detection performance, particularly in the extraction of features when dealing with targets of different scales.

2) Decoder: The role of the decoder is to combine and decode the features from the encoder, mapping them to the final output of object detection. In RLFDNet, after obtaining the feature layer output from the ECA attention mechanism, the C2f module is introduced to reduce redundant representations of convolutional kernels, significantly reducing the number of convolutions and parameters. At this point, this layer's features are passed as a branch to the Detector because it can maintain the detection of smaller objects. To better obtain high-level features and increase semantic information while considering model lightweighting, nearest neighbor upsampling is applied to the upper-level features, doubling the size of the feature map. The Conv layer receives features from the previous layer and concatenates three 1×1 convolutional layers, increasing the model's receptive field to cover a larger area of the image. Then, the corresponding scale-sized feature map extracted from the Encoder is concatenated, followed by another C2f and a 1×1 standard convolutional layer to reduce the number of parameters and computations. This portion of features is then split into two branches: one continues to concatenate the decoder for the same operations, and the other is output to the Detector for detection preparation. This design ultimately accumulates three sets of features at different scales, utilizing feature mappings of different scales for predictions, enhancing RLFDNet's perception of objects of different sizes.

3) Detector: The different-stage feature maps output from the Decoder are passed to the Detector. The main task of the Detector is to merge these feature maps and fuse the encoded information into the original feature map. It predicts the distances between each anchor point and the four edges of the target bounding box through the regression branch, determining the target's position. The Non-Maximum Suppression (NMS) is then applied to filter the generated prediction boxes. The Intersection over Union (IoU) evaluation metric is used to measure the overlap between two prediction boxes. By comparing the IoU values between prediction boxes, the model determines whether they belong to the same object, ultimately eliminating redundant detection results.

Overall, the RLFDNet model has a concise overall architecture design. Through the implementation of multi-scale feature fusion, context information aggregation, and the introduction of channel attention mechanisms, the model's perception and expressive capabilities are enhanced. This enables the model to better adapt to the detection of objects of different sizes and complexities. With minimal parameter settings, the model maintains its lightweight nature, reducing memory requirements, making it easy to deploy on low-end edge devices, and ensuring good real-time performance.

C. Loss Function

The loss function, serving as a guide for adjusting weights during backpropagation, measures the error between the forward propagation results of a neural network and the ground truth values in each iteration. In the implementation of

RLFDNet, various commonly used loss functions were explored. For the Complete Intersection over Union (CIoU) loss function [22], which functions as the bounding box loss, the calculation method is as described in Eq. (1) and Eq. (2):

$$CIoU = IoU - \frac{\rho^2\left(b, b^{g^t}\right)}{c^2} - \alpha v \quad (1)$$

$$L_{CIoU} = 1 - CIoU \quad (2)$$

IoU represents the intersection ratio of the real bounding box and the bounding box. c denotes the minimum diagonal length of the bounding box enclosing the predicted box and the ground truth box, and $\rho^2\left(b, b^{g^t}\right)$ represents the Euclidean distance between the center points of the ground truth box and the predicted box. The calculation method of α and v is shown in Eq. (3) and Eq. (4):

$$v = \frac{4}{\pi^2}\left(arctan\frac{w^{g^t}}{h^{g^t}} - arctan\frac{w}{h}\right)^2 \quad (3)$$

$$\alpha = \frac{v}{(1 - IoU) + v} \quad (4)$$

In Eq. (3), h^{g^t} and w^{g^t} represent the height and width of the ground truth box; h and w represent the height and width of the prediction box. CIoU Loss function considers the coverage area, aspect ratio, and center distance, comprehensively, which can measure its relative position well, and solve the problem of optimizing the horizontal and vertical directions of the prediction box, but this method does not consider the direction matching between the target box and the prediction box, which leads to a slow convergence speed. Thus, this paper used the Smooth Intersection over Union (SIoU) loss function [23]. SIoU introduces the optimization of the vector angle between the target box and the predicted box and plays a significant role in the strawberry detection network through a linear combination of four components: angle cost, distance cost, shape cost, and IoU cost. Its calculation method is as described in Eq. (5) and Eq. (6):

$$L_{SIoU} = 1 - IoU + \frac{\Delta + \Omega}{2} \quad (5)$$

$$IoU = \frac{\left|B \cap B^{GT}\right|}{\left|B \cup B^{GT}\right|} \quad (6)$$

where B and B^{GT} represent a prediction box and a ground truth box, Ω represents the shape cost, Δ represents the angle cost, and the distance cost is redefined. Ω and Δ are defined in Eq. (7) and Eq. (8):

$$\Omega = \sum_{t=w,h}(1 - e^{-w_t})^{\theta} \quad (7)$$

$$\Delta = \sum_{t=x,y}(1 - e^{-\gamma\rho_t}) \quad (8)$$

In Eq. (7), $w_w = \frac{\left|w-w^{g^t}\right|}{max\left(w,w^{g^t}\right)}$, $w_h = \frac{\left|h-h^{g^t}\right|}{max\left(h,h^{g^t}\right)}$, θ indicates the degree of concern for Ω.

In Eq. (8), $\rho_x = \left(\frac{\left|b_{c_x}^{g^t} - b_{c_x}\right|}{c_w}\right)^2$, $\rho_y = \left(\frac{\left|b_{c_y}^{g^t} - b_{c_y}\right|}{c_h}\right)^2$, γ is defined in Eq. (9):

$$\gamma = 1 + 2\sin^2\left(arcsin\frac{max(b_{c_y}^{g^t}, b_{c_y}) - min(b_{c_y}^{g^t}, b_{c_y})}{\sqrt{(b_{c_x}^{g^t} - b_{c_x})^2 + (b_{c_y}^{g^t} - b_{c_y})^2}} - \frac{\pi}{4}\right) (9)$$

In Eq. (9), $b_{c_x}^{g^t}$ and $b_{c_y}^{g^t}$ represent the coordinates of the ground truth bounding box's center. b_{c_x} and b_{c_y} represent the coordinates of the predicted bounding box's center.

The SIoU loss function redefines distance loss by considering vector angles between required regressions, reducing regression freedom, accelerating network convergence, and enhancing accuracy. For instance, in densely packed rice panicles, SIoU effectively distinguishes boundaries, improving detection accuracy and stability. Therefore, SIoU is advantageous for detecting dense or small targets.

III. Experiments

A. Experimental Details

In this study, rice spike images captured at different altitudes, including 7m, 12m, and 20m, were used to evaluate the RLFDNet model. The detailed dataset information is shown in Table I, and images at each altitude were randomly divided into training, validation, and test sets in a ratio of 6:1:3. The experiments were implemented using the PyTorch deep learning framework [24] and accelerated with CUDA. Since each image's size was 512×512 pixels, inputting the model with the original image size maintained a low resolution, aligning more with the requirements of edge devices. To ensure the objectivity of results, all methods were trained and tested under the same configuration. During training, the batch size was set to 16, the learning rate was initialized to 0.01, Stochastic Gradient Descent (SGD) optimizer was used with a momentum factor of 0.937, and weight decay was set to 5×10^{-4}. To prevent overfitting and enhance model robustness, data augmentation techniques were applied, including color distortion, random translation, random flipping, random scaling, and random cropping. After configuring the relevant parameters, the RLFDNet model was optimized for 300 epochs based on convergence speed considerations.

B. Evaluation Metrics

When establishing a detection model, both precision and recall need to be considered. Therefore, this study used metrics such as Precision, Recall, F1-score, mAP@0.5, and mAP@0.5:0.95 to assess the model's performance and evaluate the detection results. The calculation methods for Precision, Recall, and F1-score are given by Eq. (10) to Eq. (12):

$$\mathrm{P} = \frac{TP}{TP+FP} \quad (10)$$

$$\mathrm{R} = \frac{TP}{TP+FN} \quad (11)$$

$$F1 = 2 \times \frac{P \times R}{P + R} \quad (12)$$

where, P represents precision, R represents recall, and F1 represents F1-score. TP (True Positive) denotes the number of positive samples correctly classified, TN (True Negative) represents the number of negative samples correctly classified. FP (False Positive) indicates the number of negative samples incorrectly classified as positive, while FN (False Negative) represents the number of positive samples incorrectly classified as negative.

The mean Average Precision (mAP) represents the overall performance at different IoU thresholds, including mAP@0.5 and mAP@0.5:0.95. Here, mAP@0.5 denotes the average mAP at an IoU threshold of 0.5, with a higher value indicating higher detection accuracy for that category. mAP@0.5:0.95 represents the average mAP across different IoU thresholds (ranging from 0.5 to 0.95 with a step size of 0.05), providing a more stringent evaluation of the model's performance. The calculation method for mAP is given by Eq. (13):

$$mAP = \frac{1}{n}\sum_{1}^{n} P(R)d(R) \qquad (13)$$

where, n is the number of classes, in this experiment, there is only one class, which is rice spikes, so n=1. In addition, since the distribution of rice spikes is dense, evaluating counting performance is also meaningful. Here, three metrics are used to assess the consistency between predicted and true values, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2). Specifically, they are defined by the following Eq. (14) to Eq. (16):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\widehat{y_i} - y_i| \qquad (14)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\widehat{y_i} - y_i)}^{2} \qquad (15)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\widehat{y_i} - y_i)^2}{\sum_{i=1}^{n}(\overline{y_i} - y_i)^2} \qquad (16)$$

where, n is the number of samples, y_i is the true count, $\widehat{y_i}$ is the predicted count, and $\overline{y_i}$ is the mean of the true counts. These metrics provide a quantitative assessment of the model's ability to accurately predict the count of rice spikes. The result of R^2 falls within the range [0, 1], indicating the proportion of the variance in the predicted values to the variance in the actual values near the mean. This metric can be interpreted as the goodness of fit of the model, where 1 represents a perfect fit, and 0 indicates no linear relationship between the actual counts and the predicted values.

C. *Analysis of Counting Performance of RLFDNet*

To comprehensively evaluate the performance of the RLFDNet model across different altitudes (7m, 12m, and 20m), the model was trained and tested on each dataset, and the experimental results are presented in Table II.

Furthermore, Fig. 3 illustrates a linear regression plot, which is an indispensable tool in the analysis of counting task experiments. It visually presents the counting performance differences between RLFDNet model inference and manual counting. A closer alignment of points to the perfect prediction line indicates better model fitting. The results show that the model performs exceptionally well at 7m altitude, demonstrating more accurate predictions and higher model fitting (R^2=0.9461). Conversely, at altitudes of 12m and 20m, the model's performance slightly decreases, showing larger MAE, RMSE, and slightly lower R^2, indicating potential challenges in predicting at these two altitudes.

A deeper investigation into the performance differences at different shooting heights and discussion of the possible reasons for these differences were conducted. The variations in this regard are mainly influenced by two key factors: shooting height and environmental conditions. Firstly, changes in shooting height directly affect the size and resolution of panicles in the images. At lower altitudes, panicles are relatively larger and easier for the model to capture details. At higher altitudes, smaller panicles increase the difficulty of detection. Secondly, lighting conditions also vary at different altitudes, leading to varying degrees of light and shadow in the images. Uniform lighting at lower altitudes facilitates the model in capturing the edges and details of panicles. Conversely, lighting conditions at higher altitudes may be more complex, adding to the difficulty of model inference.

At the same time, Fig. 4 illustrates images with the highest prediction errors in each dataset. Ground Truth (GT) is represented by red points in the images, indicating manual counting results, while Predicted (PD) is indicated by red boxes in the inference images, representing the model's inference results. This aids in understanding the potential reasons behind these inaccuracies. Clearly, these images confirm a common notion that they mostly contain significant environmental noise. Factors such as differences in lighting, small target sizes, and high density significantly increase the difficulty of detection. In some cases, even experienced human experts may find identifying spikes challenging. A comprehensive evaluation of counting performance across the entire dataset will be further discussed in the next section.

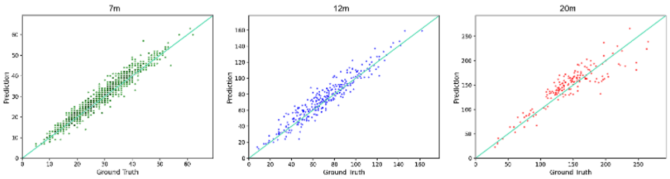

Fig. 3. The linear regression graph, illustrating the variance between counting results of RLFDNet model and human counting.

TABLE II. RLFDNET'S COMPREHENSIVE PERFORMANCE ACROSS ALTITUDES

GSD	P	R	mAP@0.5	mAP@0.5:0.95	MAE	RMSE	R^2
GSD_{7m}	0.915	0.923	0.961	0.691	1.86	2.49	0.946
GSD_{12m}	0.830	0.813	0.861	0.423	6.97	9.07	0.906
GSD_{20m}	0.871	0.839	0.907	0.614	15.26	19.29	0.816

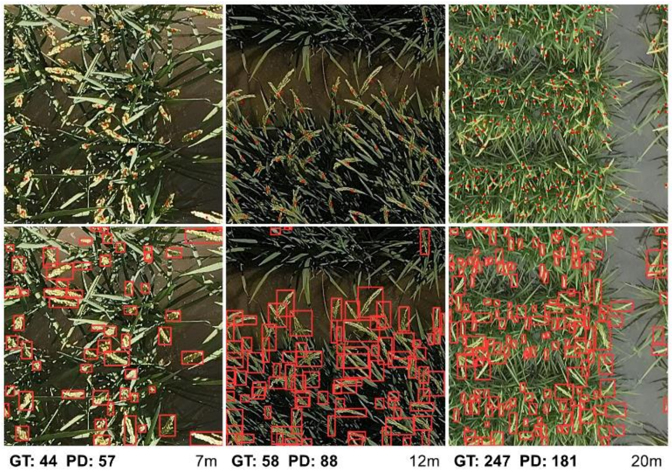

Fig. 4. Images with the maximum errors at each altitude. (GT: Red points - manual counting results; PD: Red boxes - RLFDNet's inference results).

D. Comparison with different Object Detection Method

To compare the superiority of the RLFDNet model, six advanced and commonly used object detection models, including YOLOv5 [25], YOLOv7-tiny [26], YOLOv8 [21], CenterNet [27], Faster R-CNN [28], and SSD [29], were selected for a comprehensive analysis of evaluation performance, counting performance, and model lightweighting. To ensure fair and objective results, they were trained and tested on identical training, validation, and test sets for each altitude dataset. Although this effort was substantial, it was meaningful, providing insights into the differences between different models and presenting results more objectively.

1) Performance comparison: The results of the evaluation performance for different models are presented in Table III. Upon examination of the test results, RLFDNet demonstrated satisfactory counting performance. While YOLOv8's results were very close, even surpassing RLFDNet in one metric at altitudes 12m and 20m, the difference was marginal. Overall, RLFDNet outperformed its counterparts. Conversely, other models exhibited slightly inferior performance in detecting rice panicles at each altitude, particularly Faster R-CNN and SSD. This suggests that these models may lack robustness when dealing with smaller targets or more complex conditions, hindering their ability to achieve highly accurate object detection.

2) Counting performance comparison: Furthermore, a detailed analysis of counting performance was conducted for each altitude dataset, and the experimental results are presented in Table IV. Observations revealed that YOLOv8, CenterNet, and RLFDNet consistently demonstrated stable prediction performance at each altitude, with RLFDNet maintaining the optimal performance. On the other hand, Faster R-CNN and SSD exhibited higher errors and lower fitting accuracy at higher altitudes, corroborating the results of the performance evaluation. These models faced challenges in object detection when dealing with smaller targets or more complex environments. In contrast, RLFDNet maintained relatively good and stable performance even at higher altitudes with smaller targets and higher density. The experiments indicate that RLFDNet exhibits strong generalization and robustness in counting performance.

TABLE III. COMPARISON OF EVALUATION PERFORMANCE ACROSS DIFFERENT MODELS

GSD	Model	F1	mAP@0.5	mAP@0.5:0.95
GSD$_{7m}$	YOLOv5	0.835	0.884	0.528
	YOLOv7-tiny	0.870	0.923	0.609
	YOLOv8	0.919	0.959	0.675
	CenterNet	0.600	0.958	0.756
	Faster R-CNN	0.647	0.654	0.635
	SSD	0.478	0.513	0.463
	RLFDNet	0.942	0.961	0.691
GSD$_{12m}$	YOLOv5	0.818	0.956	0.409
	YOLOv7-tiny	0.554	0.674	0.397
	YOLOv8	0.819	0.860	0.428
	CenterNet	0.638	0.793	0.432
	Faster R-CNN	0.493	0.392	0.364
	SSD	0.317	0.352	0.269
	RLFDNet	0.821	0.861	0.423
GSD$_{20m}$	YOLOv5	0.835	0.883	0.525
	YOLOv7-tiny	0.554	0.678	0.466
	YOLOv8	0.862	0.909	0.608
	CenterNet	0.656	0.877	0.566
	Faster R-CNN	0.369	0.237	0.192
	SSD	0.340	0.361	0.267
	RLFDNet	0.872	0.907	0.614

TABLE IV. COMPARISON OF COUNTING PERFORMANCE ACROSS DIFFERENT MODELS AT VARIOUS ALTITUDES

GSD	Model	MAE	RMSE	R^2
GSD$_{7m}$	YOLOv5	12.38	18.88	0.829
	YOLOv7-tiny	4.04	5.24	0.868
	YOLOv8	1.70	2.98	0.943
	CenterNet	1.70	2.93	0.942
	Faster R-CNN	10.74	11.67	0.843
	SSD	5.84	7.65	0.677
	RLFDNet	1.86	2.49	0.946
GSD$_{12m}$	YOLOv5	6.59	9.65	0.900
	YOLOv7-tiny	8.18	10.59	0.846
	YOLOv8	10.00	12.80	0.873
	CenterNet	9.61	12.12	0.883
	Faster R-CNN	18.51	21.55	0.653
	SSD	28.66	32.87	0.660
	RLFDNet	6.97	9.07	0.906
GSD$_{20m}$	YOLOv5	15.76	23.60	0.816
	YOLOv7-tiny	23.31	29.65	0.549
	YOLOv8	15.34	21.85	0.812
	CenterNet	19.72	24.91	0.696
	Faster R-CNN	27.34	35.57	0.302
	SSD	33.81	42.16	0.195
	RLFDNet	15.26	19.29	0.816

3) Model lightweight comparison: After evaluating model performance metrics and counting performance, it is crucial to consider another key factor in the design of the RLFDNet model – achieving lightweightness. To assess different models, the number of parameters (Params) is used to reflect the total trainable parameters in the network, indicating model complexity and its capacity to learn and represent features. The calculation is defined by Eq. (17):

$$Params = [i \cdot (k \cdot k) \cdot o] + o \qquad (17)$$

where, i is the input size, k is the convolution kernel size, and o is the output size. Regarding inference efficiency, the evaluation is conducted using the Frames per Second (FPS) metric to reflect the model's inference speed. A higher FPS indicates a faster generation of inference results. The calculation is defined by Eq. (18):

$$FPS = \frac{1000}{pre{-}process + inference + NMS} \qquad (18)$$

Here, pre-process, inference, NMS is pre-processing, inference, and Non-Maximum Suppression time, respectively for each image.

In this experiment, RLFDNet's efficiency is compared with different models. FPS measures the number of image frames the model can process per unit time, while Params is a direct measure of model complexity and an important constraint for deployment. The tests were conducted on an NVIDIA GTX1080Ti GPU (8G) device, a lower-end GPU with slower computational speed. The results are shown in Fig. 1. It is evident that RLFDNet achieves an excellent overall performance. Compared to YOLOv5, which is relatively close in performance, RLFDNet has only 4% more Params, while the FPS has increased by 70%, reaching 80.43 frames per second. This improvement is significant, as it maintains a relatively small total parameter count while substantially enhancing inference efficiency. It contributes greatly to deploying the model on low-end edge devices. The size of the model's parameter count directly impacts whether individuals with budget-friendly devices can enjoy the benefits of advanced technology, especially in resource-constrained fields such as agriculture, where edge devices, embedded systems, and mobile robots provide practitioners with more decision support and production management tools.

IV. Discussion

This study introduces the RLFDNet model, offering a lightweight and real-time method for rice panicle localization and counting. The model leverages the lightweight backbone CSPDarknet and introduces an innovative strategy in the design, maintaining a relatively low image resolution in experiments to meet the requirements of edge devices, achieving high accuracy and lightweight characteristics. As shown in Fig. 5, the model accurately localizes and counts rice panicles in four crucial growth stages at different shooting heights of 7m, 12m, and 20m. Moreover, RLFDNet demonstrates good robustness and adaptability when facing common natural factors in the field, such as strong sunlight, overcast conditions, and interferences like mutual occlusion, varied panicle poses, changes in lighting conditions, and water reflections, as depicted in Fig. 6.

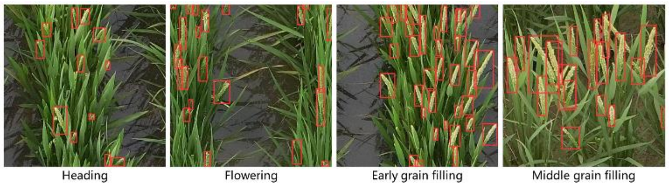

Fig. 5. Rice panicle detection results at four different growth stages (Example at 7m altitude).

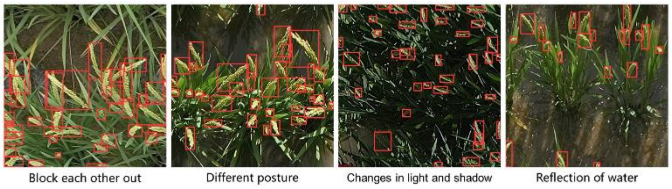

Fig. 6. Detection results of rice panicles in the face of various influencing factors (Example at 7m altitude).

In summary, RLFDNet's design incorporates several key innovations:

1) Multi-Scale receptive fields and feature fusion: RLFDNet employs a pyramid network architecture in the encoder to capture multi-scale information effectively. Different convolutional layers' receptive fields help in understanding spatial object relationships, while a feature fusion mechanism integrates features from various scales to enhance dense target detection.

2) Reinforcement learning-guided object detection: RLFDNet dynamically adjusts its object detection strategy during training using reinforcement learning mechanisms. This adaptive approach helps the model better adapt to changes in altitudes and environmental conditions, enhancing performance in complex scenes.

3) Attention mechanism integration: RLFDNet incorporates attention mechanisms at the connections between the encoder and decoder, allowing the model to adaptively focus on important regions in the image. By introducing attention mechanisms, the model learns the importance of target regions during training, improving the precision of target localization and counting accuracy.

4) Lightweight design: Prioritizing lightweight design for feasible deployment on edge devices, RLFDNet reduces the total number of network parameters, enhancing the model's inference efficiency. This design decision maintains counting performance while strengthening the model's adaptability in resource-constrained environments.

5) Environmental adaptability: Experimental details consider different shooting heights and environmental conditions, with the model employing a self-adaptive adjustment strategy. Learning richer features under varying conditions enhances adaptability to complex scenarios, crucial for practical rice panicle counting applications.

However, while RLFDNet significantly outperforms other advanced object detection methods in both accuracy and inference efficiency, it acknowledges certain limitations. Firstly, as the experiments were conducted at three specific altitudes (7m, 12m, and 20m), real-world applications may involve different shooting heights not covered in this study, potentially affecting inference results due to variations in panicle size and density. Secondly, variations in rice panicle phenotypes due to different rice varieties in different regions could result in suboptimal inference performance, highlighting the need for further research in addressing these limitations.

V. Conclusion

In this research, rice panicle localization and counting method named RLFDNet was designed and proposed. A concise and efficient encoder-decoder module was further developed within the model. A series of experiments demonstrated that RLFDNet achieved excellent results in rice panicle detection at different shooting heights, providing real-time and accurate localization and counting of rice panicles. With an MAE of 1.86 and an R^2 of 0.9461, the model showed robust performance. Considering various altitudes, the model achieved an average accuracy of mAP@0.5 at 0.91, with a total parameter count of only 4.40M. The inference efficiency reached 80.43 FPS, meeting the requirements for deployment on low-end edge devices. This provides a valuable tool for farmers and governments in assessing rice yields. In the future, exploration will be conducted to test the model with more shooting heights and different rice varieties to expand its capability to adapt to diverse environmental conditions, such as varying lighting and weather patterns, thereby enhancing its adaptability and reliability in real agricultural settings. The aim is to broaden its applicability across different countries and regions while addressing emerging challenges in agricultural technology.

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Integrating Taguchi Method and Support Vector Machine for Enhanced Surface Roughness Modeling and Optimization

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***Abstract*—End milling process is widely used in various industrial applications, including health, aerospace and manufacturing industries. Over the years, machine technology of end milling has grown exponentially to attain the needs of various fields especially in manufacturing industry. The main concern of manufacturing industry is to obtain good quality products. The machined products quality is commonly correlated with the value of surface roughness (Ra), representing vital aspect that can influence overall machining performance. However, finding the optimal value of surface roughness is remain as a challenging task because it involves a lot of considerations on the cutting process especially the selection of suitable machining parameters and also cutting materials and workpiece. Hence, this study presents a support vector machine (SVM) prediction model to obtain the minimum Ra for end milling machining process. The prediction model was developed with three input parameters, namely feed rate, depth of cut and spindle speed, while Ra is the output parameter. The data of end milling is collected from the case studies based on the machining experimental with titanium alloy, workpiece and three types of cutting tools, namely uncoated carbide WC-Co (uncoated), common PVD-TiAlN (TiAlN) and Supernitride coating (SNTR). The prediction result has found that SVM is an effective prediction model by giving a better Ra value compared with experimental and regression results.**

Keywords—Support Vector Machine; surface roughness; end milling; Taguchi method

I. Introduction

A. Problem Background

In recent years, the machining process becomes important and widely used in manufacturing industries. With the highly competitive industries that have emerged nowadays, manufacturers compete with each other in delivering products of high quality with lower production costs. The effectiveness of the machining process relies on selecting appropriate cutting conditions, which is normally done by the machinists. Machining refers to a process of material removal from a workpiece in a chip form. Machining can be either conventional or non-conventional machining. Non-conventional machining is also considered as modern machining. The popular machining performances evaluated by the significant measure are surface roughness (Ra), tool wear, cutting force, strength, torque, chip shape, etc. Pan et al., [1] found that the machining performance that garnered the most attention from researchers is Ra. Ra is considered as a key factor to determine the surface quality of a product. This is due to the significant role of Ra in the performance of machine parts for wear resistance, ductility, tensile, and fatigue. Ra has a major effect on dimensional accuracy, mechanical parts efficiency and cost of production. Furthermore, Ra also affects the machining process stability diagnosis where a reduction of the surface quality can imply non-homogeneity of the workpiece surface, progressive wear of the tool and cutting tool chatter [2].

Ra is a product's measurement for technological quality and a feature that affects the production cost. Due to the advent development of technology, such as computing capability and data science, the researchers prefer to apply computational approaches to model the machining process [3]. Furthermore, due to the uncertainty and complexity of Ra, it is quite difficult to obtain the Ra value by the analytical equations. Computational approaches, including machine learning (ML) methods have become most interesting area of study, and researchers have shown tremendous interest in developing various models to improve the efficiency of measuring machining performances. ML approaches are capable to solve the optimal solution problem of the machining parameters with either the minimum or maximum machining performance. ML approaches that have been considered by previous studies include Support Vector Machine (SVM) [4]-[5], Artificial Neural Network (ANN) [6] – [7], Bayesian Network [8]-[9], Decision Tree [10], Random Forest [11], etc.

The key problem in the machining process is how to use various cutting conditions and machining parameters to achieve optimum solutions for the machining performances. These optimal solutions must be capable of minimizing the economic aspects of machining operations. Traditionally, during the machining process, the parameter selection for the cutting conditions was usually left to the machinist. However, this approach also relies on the machinist's skills. Furthermore, this traditional way of cutting method requires high production costs due to the fact that the material can only be used once. Machinists' experience also plays an important role, but often the optimum values for each experiment are difficult to preserve [12]. Hence, there is a need for the development of the computational approaches method in order to solve this problem. The technology growth has brought the ML approaches to be introduced to develop an improved model for the performances of the machining process. Using ML, it is easy to implement machine modelling instead of conventional techniques which are required a more complex physical understanding and knowledge of the machining process. The machining process can be completed in different approaches with the same objectives with the help of ML.

B. Proposed Prediction Model

This study proposed the integration of ML approach with Taguchi Method to prediction machining performance of end milling process. Selected ML approach, which is SVM is applied to estimate a minimum value of Ra in one of the mostly used machining process. SVM is based on the classifier of statistical learning theories [13]. SVM has demonstrated its capability when it delivered a better performance than ANN [14]. SVM has been widely applied in various fields such as health [15]-[16], agriculture [17]-[18], geology [19], and etc. In machining field, SVM has been extensively applied in various studies for the prediction of machining performances in conventional and non-conventional machining.

SVM was proven to give an effective prediction model for several of machining processes. Kumar et al [20] developed prediction models of Ra, cutting force, tangential force and tool wear in the boring process using SVM and response surface methodology (RSM). The machining experiment was carried out using full factorial design with workpiece AISI 4340 steels and multi-layered coated carbide electrode. The result shows that SVM has outperformed RSM for the prediction of machining parameters with the RMSE value of 0.039. Singh et al [21] applied SVM to predict the Ra value for the wired EDM (WEDM) process. The parameters namely servo voltage, pulse on time, pulse off time and peak current were used to develop a model. The experiment was carried out based on 3^k full factorial design. The prediction results show the minimum Ra value can be achieved using SVM approach.

Do Duc et al. [22] predicted the Ra value of 3X13 steel material in CNC hole turning process. The machining experimental was conducted based on DOE with feed rate, cutting speed, tool nose radius and cutting depth as the input parameters. The prediction models of RSM and SVM were developed, and results show that SVM model has outperformed RSM model by giving the mean absolute error (MAE) and mean square error (MSE) of 2.80 % and 0.17 %, respectively. Ramesh and Mani [23] applied SVM to predict the Ra value of abrasive waterjet milling (AWM) process. The experiments were carried out based on the RSM with Box-Behnken method. The input parameters were used to model the Ra are abrasive flow rate, pressure, the step over and the traverse rate. The optimal parameter values are then applied in the ε- SVM model to determine the minimum Ra in the AWM. The prediction result shows significant value of the training data accuracy. The prediction model then improved by tuning its hyperparameters using the fivefold cross validation. The result shows that SVM model has outperformed the quadratic regression model by giving accuracy of 92.4% compared to 70%.

From the review of the previous studies implemented by previous researchers, it can be concluded that SVM is able to give effective prediction results for conventional and modern machining processes. Furthermore, SVM has outperformed other techniques such as RSM and ANN [20], [24]. In the current work, the SVM prediction model is developed to predict the Ra value for end milling processes.

The remainder of this article is organized as follows. Section II discussed the materials and method of the study. It consists of experimental data and the approaches used in this study. Furthermore, the result and discussion were discussed in Section III and finally the conclusion is stated in Section IV.

II. Materials and Method

A. Experimental Data

The data used for the SVM prediction model is based on the actual machining experimental conducted by Mohruni [25]. The experiment was carried out using annealed alpha–beta titanium alloy workpiece and three types of cutting tools; “uncoated carbide WC-Co” (uncoated), “common PVD-TiAlN” (TiAlN) and “Supernitride coating” (SNTR). Cutting speed, feed rate and depth of cut were used as input parameters while Ra was the output parameter. The experiment was conducted based on a 2^3 factorial design. Table I shows the coded value ranges for each of the input parameters. The range values of coded parameters are levels -1, 0, and 1. The experimental data for surface roughness value which is measured using Taylor Hobson Surfronic +3, is given in Table II.

B. Taguchi Method

The experimental data as in Table II were analyzed based on the Taguchi method to obtain the significant parameters for the Ra values. The signal-to-noise (S/N) ratio of the Taguchi method was used as the quality characteristic of the parameters. Instead of standard deviation, the S/N ratio is used as a measurable value given the fact that the standard deviation often decreases as the mean decreases, and increases when the mean increases. This implies that it is impractical to minimize the standard deviation and get the mean target first. According to Salur et al., S/N ratio theory operates in two directions; reduction of variance and mean improvement. In addition, the S/N ratio is correlated with the impact of the factors on the response.

The S/N ratio value is computed based on performance characteristics whether it is larger-the-better, smaller-the-better or nominal-the-better, using Eq. (1) – Eq. (3).

Smaller-the-better:

$$S/N = -\log 10\ [\tfrac{1}{n}\sum_{i=1}^{n} y_i^2] \tag{1}$$

Larger-the-better:

$$S/N = -\log 10\ [\tfrac{1}{n}\sum_{i=1}^{n} \tfrac{1}{y_i^2}] \tag{2}$$

Nominal-the-better:

$$S/N = 10 \log\ [\tfrac{y}{s_y^2}] \tag{3}$$

TABLE I. THE RANGE VALUE OF END MILLING PARAMETERS

Variables	Unit	Levels in coded form				
		−1.4142	−1	0	+1	+1.4142
Cutting speed (V)	(m/min)	124.53	130	144.22	160	167.03
Feed rate (F)	(mm/ tooth)	0. 025	0.03	0.046	0.07	0.083
Radial rake angle (°)	γ	6.2	7	9.5	13	14.8

TABLE II. EXPERIMENTAL DATA FOR SURFACE ROUGHNESS

No	Experimental process setting values			Ra (μm) Experimental		
	V (m/min)	F (mm/tooth)	γ (°)	Un-coated	TiAlN coated	SNTR coated
1	130	0.03	7	0.365	0.32	0.284
2	160	0.03	7	0.256	0.266	0.196
3	130	0.07	7	0.498	0.606	0.668
4	160	0.07	7	0.464	0.476	0.624
5	130	0.03	13	0.428	0.26	0.28
6	160	0.03	13	0.252	0.232	0.19
7	130	0.07	13	0.561	0.412	0.612
8	160	0.07	13	0.512	0.392	0.576
9	144.22	0.046	9.5	0.464	0.324	0.329
10	144.22	0.046	9.5	0.444	0.38	0.416
11	144.22	0.046	9.5	0.448	0.46	0.352
12	144.22	0.046	9.5	0.424	0.304	0.4
13	124.53	0.046	9.5	0.328	0.36	0.344
14	124.53	0.046	9.5	0.324	0.308	0.32
15	167.03	0.046	9.5	0.236	0.34	0.272
16	167.03	0.046	9.5	0.24	0.356	0.288
17	144.22	0. 025	9.5	0.252	0.308	0.23
18	144.22	0. 025	9.5	0.262	0.328	0.234
19	144.22	0.083	9.5	0.584	0.656	0.64
20	144.22	0.083	9.5	0.656	0.584	0.696
21	144.22	0.046	6.2	0.304	0.3	0.361
22	144.22	0.046	6.2	0.288	0.316	0.36
23	144.22	0.046	14.8	0.316	0.324	0.368
24	144.22	0.046	14.8	0.348	0.396	0.36

where, *n* is a sample size and *y* is a sample value with i=1, 2, 3...n. Surface roughness value targets the minimum value for better performance, hence it applies the "smaller-the-better". Table III shows the S/N ratio for uncoated, TiAlN and SNTR end milling.

Based on the S/N ratio value in Table III, mean response table was developed for each level for all machining parameters. The ranking was determined for machining parameters at every level by considering the difference between the highest and lowest values. The higher rank shows that the Ra value is more affected by the parameter. Table IV shows the response table for Ra of uncoated end milling.

TABLE III. S/N RATIO FOR UNCOATED, TIALN AND SNTR

No.	Un-coated	S/N Ratio	TiAIN coated	S/N Ratio	SNTR coated	S/N Ratio
1	0.365	8.754	0.32	9.897	0.284	10.934
2	0.256	11.835	0.266	11.502	0.196	14.155
3	0.498	6.055	0.606	4.351	0.668	3.504
4	0.464	6.670	0.476	6.448	0.624	4.096
5	0.428	7.371	0.26	11.701	0.28	11.057
6	0.252	11.972	0.232	12.690	0.19	14.425
7	0.561	5.021	0.412	7.702	0.612	4.265
8	0.512	5.815	0.392	8.134	0.576	4.792
9	0.464	6.670	0.324	9.789	0.329	9.656
10	0.444	7.052	0.38	8.404	0.416	7.618
11	0.448	6.974	0.46	6.745	0.352	9.069
12	0.424	7.453	0.304	10.343	0.4	7.959
13	0.328	9.683	0.36	8.874	0.344	9.269
14	0.324	9.789	0.308	10.229	0.32	9.897
15	0.236	12.542	0.34	9.370	0.272	11.309
16	0.24	12.396	0.356	8.971	0.288	10.812
17	0.252	11.972	0.308	10.229	0.23	12.765
18	0.262	11.634	0.328	9.683	0.234	12.616
19	0.584	4.672	0.656	3.662	0.64	3.876
20	0.656	3.662	0.584	4.672	0.696	3.148
21	0.304	10.342	0.3	10.458	0.361	8.850
22	0.288	10.812	0.316	10.006	0.36	8.874
23	0.316	10.006	0.324	9.789	0.368	8.683
24	0.348	9.168	0.396	8.046	0.36	8.874

TABLE IV. RESPONSE TABLE FOR UNCOATED

Parameters	Cutting speed	Feed rate	Radial rake angle
Level			
Level -1	1.1334	1.6638	1.3881
Level -1.4142	0.8113	0.9836	0.8814
Level 0	4.1840	4.7036	4.3541
Level 1	1.5122	0.9817	1.2575
Level 1.4142	1.0391	0.3473	0.7989
Max-Min	3.3727	3.7219	3.4727
Rank	3	1	2

From Table IV, the feed rate is ranked first, followed by radial rake angle and cutting speed. Hence, it can be concluded that, feed rate is the most significant parameter while cutting speed is the least significant parameter for uncoated end milling. The optimal level for surface roughness value of uncoated end milling can be determined based on main effects plot, as shown in Fig. 1.

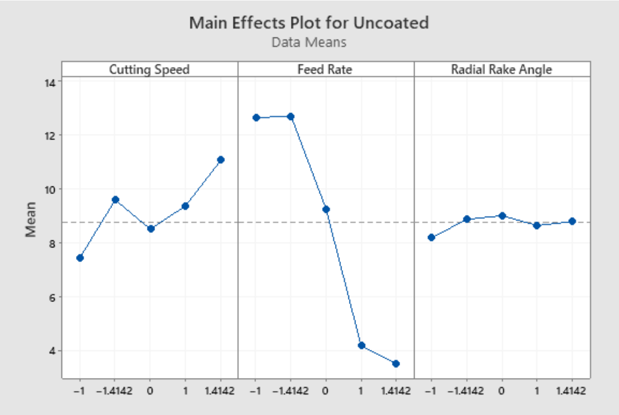

Fig. 1. Main effects plot for uncoated.

Based on the plot, it shows that the optimal solution of Ra for uncoated end milling is where cutting speed at level 1.4142 with 167.03 m/min, feed rate at level -1.4142 with 0.025 mm/tooth and input parameters radial rake angle at level 0 with 9.5°. Table V shows the response table for TiAlN. The table shows that input parameter feed rate is ranked first, trailed by input parameters cutting speed and radial rake angle. Hence, it can be concluded that feed rate is the most significant parameter while radial rake angle is the least significant parameter for TiAlN end milling. The optimal level for surface roughness value of TiAlN end milling can be determined from the main effects plot, as in Fig. 2.

From Fig. 2, the optimal solution can be determined for each of the parameters. The optimal level for TiAlN is where the input parameter cutting speed is at level 1 with 160 m/min, input parameter feed rate at level -1 with 0.03 mm/tooth and input parameter radial rake angle at level -1.4142 with 14.8°. Table VI shows the response table for SNTR and Fig. 3 shows the optimal level for surface roughness value of SNTR.

From Fig. 3, the optimal solution for SNTR can be determined for each of the parameters. The optimal level for SNTR is where the input parameter cutting speed is at level 1.4142 with 167.03 m/min, input parameter feed rate at level -1.4142 with 0.025 mm/tooth and input parameter radial rake angle at level 0 with 9.5°. Based on the response tables for uncoated, TiAlN and SNTR, it can be concluded that feed rate is the most significant parameter for end milling machining process. Feed rate ranked first for all these three coatings. Based on the main effects plots, the optimal level for end milling differs for each of the coating's types.

C. *Support Vector Machine (SVM)*

SVM was initially proposed by Vapnik [13]. Adapting the concept of Structural Risk Minimization (SRM), SVM is able to obtain rules for decision-making and allow minor errors in setting independent tests so that learning problems can be effectively solved. Basically, SVM prediction model consists of five major steps, which are illustrated in Fig. 4.

The basic SVM regression function theory is presented in Eq. (4) [13].

$$y = f\,(x) = \rceil .\ x + b \qquad (4)$$

TABLE V. RESPONSE TABLE FOR TIALN

Parameters	Cutting speed	Feed rate	Radial rake angle
Level			
Level -1	1.4021	1.9079	1.3416
Level -1.4142	0.7960	0.8297	0.8527
Level 0	4.2895	4.6728	4.2071
Level 1	1.6156	1.1098	1.6761
Level 1.4142	0.7642	0.3473	0.7899
Max-Min	3.5253	4.3256	3.4172
Rank	2	1	3

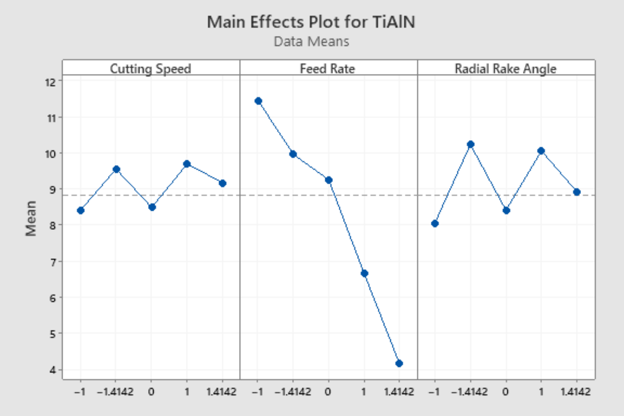

Fig. 2. Main effects plot for TiAlN.

TABLE VI. RESPONSE TABLE FOR SNTR

Parameters	Cutting speed	Feed rate	Radial rake angle
Level			
Level -1	1.2400	2.1071	1.3620
Level 1.4142	0.7986	1.0575	0.7385
Level 0	4.2495	4.6196	4.4998
Level 1	1.5612	0.6940	1.4391
Level 1.4142	0.9217	0.2927	0.7315
Max-Min	3.0095	3.9255	3.1377
Rank	3	1	2

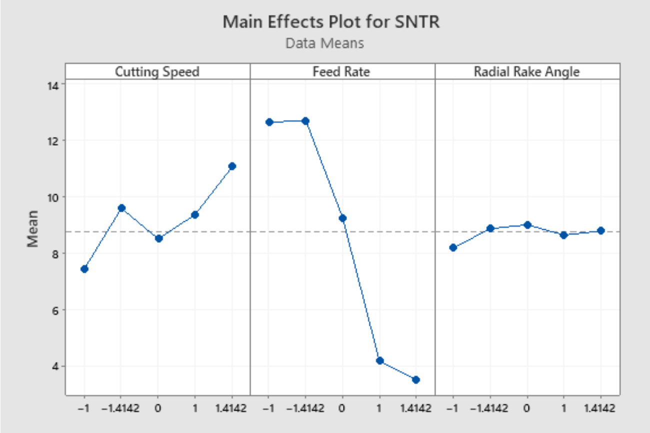

Fig. 3. Main effects Plot for SNTR.

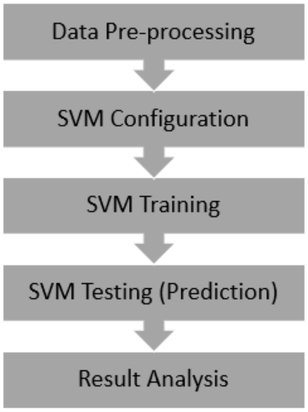

Fig. 4. Steps in SVM.

where, ω is a weight vectors, x is multivariate input, b is a bias, and y is a scalar output. Then, slack variables $\xi_i and\ \xi_i^*$ are introduced to the equation, the SVM model is expressed as:

Minimize

$$\phi(\omega) = \frac{1}{2}||\omega||^2 - C\sum_{i=1}^{n}(\xi_i - \xi_i^*) \cdot C \geq 0$$

$$y - \omega x - b \leq \varepsilon + \xi,$$

Subject to

$$\omega x - b - y \leq \varepsilon + \xi_i^*, \quad i = 1,2,\ldots,l$$

$$\xi_i, \xi_i^* \geq 0, \tag{5}$$

where, ε is a loss function, and C is a regularization parameter.

$$y = f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)(x_i \cdot x) + b \tag{6}$$

SVM model solution is obtained by applying the Lagrange Multiplier method as the following equations:

$$L(\omega, b, \xi, \xi^*) = \frac{1}{2}\ ||\omega||^2 + C\ \sum_{i=1}^{n}(\xi_i - \xi_i^*) - \sum_{i=1}^{n}\alpha_i(\varepsilon_i + \xi_i - y_i + \omega \cdot x_i + b) - \sum_{i=1}^{n}\alpha * (y_i + \varepsilon_i + \xi_i - \omega \cdot x_i - b) - \sum_{i=1}^{n}(\eta_i\xi_i + \eta_i^*\xi_i^*) \tag{7}$$

where, $\alpha_i, a_i^*, \eta_i, \eta_i^*$ are the Lagrange Multiplier. Then, the dual problem is:

Maximize

$$Q(\alpha) = \sum_{i=1}^{n} y(\alpha_i - \alpha_i^*) - \varepsilon\sum_{i=1}^{n}(\alpha_i - a_i^*) - \frac{1}{2}\sum_{i=1}^{n}(a_i - a_i^*)(x_i - x_j) \tag{8}$$

Subject to

$$\{\sum_{i=1}^{n} y_i(a_i - a_i{}^*) = 0, 0 \leq a_i \leq 0, \quad 0 \leq a_i{}^* \leq 0,$$

$$i = 1,2,\ldots,n$$

Regression function:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i{}^*)(x_i, x) + b \tag{9}$$

Nonlinear regression function:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i{}^*)\, K(x_i, x) + b \tag{10}$$

The solution of K (x_i, x) in the Eq. (9) can be changed into K(x_i,x) = (∏(x_i),⎞(x)) when using a mapping function. From the equation, *n* is the number of support vectors, K is a kernel function and b is bias. The high-accuracy prediction and good SVM model come with a proper parameter setting. RBF kernel function is used in this paper to predict the Ra of the end milling machining process.

For the SVM data pre-processing, the machining experimental dataset is divided into two datasets: one is for training and the other one is for testing that will be used to get the prediction result. The input data of training and testing data need to be transformed into a sparse format in range [0, 1]. For the SVM configuration, kernel function, Gamma value (for RBF kernel) and regularization parameter C need to be considered. The process of trial and error with different parameter values must be implemented accordingly to get the best prediction model. After completing the training and testing process, the prediction result is analyzed using statistical analysis.

III. Result and Discussion

The SVM prediction models were developed and three models were identified as the best prediction model for all three cutting tools. The models were chosen based on the highest correlation values of developed SVM models. Table VII shows the predicted Ra value of regression based on the result from Zain et al. and SVM.

TABLE VII. RA Values of Predicted Regression and SVM Predictions

No	Predicted *Ra* (µm) Regression			Predicted *Ra* (µm) SVM		
	Uncoated	TiAlN coated	SNTR coated	Uncoated	TiAlN coated	SNTR coated
1	0.306	0.304	0.259	0.2535	0.2633	**0.1372**
2	**0.226**	0.278	0.207	0.2535	0.2633	0.1372
3	0.533	0.519	0.607	0.2752	0.7957	0.8273
4	0.453	0.493	0.554	0.2752	0.7957	0.8273
5	0.334	0.270	0.250	0.1766	0.3022	0.3935
6	0.254	**0.245**	0.197	0.1766	0.3022	0.3935
7	0.561	0.486	0.597	0.7708	0.3430	0.4042
8	0.481	0.460	0.545	0.7708	0.3430	0.4042
9	0.370	0.364	0.369	0.2975	0.3483	0.3798
10	0.370	0.364	0.369	0.2975	0.3483	0.3798
11	0.370	0.364	0.369	0.1272	0.3483	0.3798
12	0.370	0.364	0.369	**0.1272**	0.3483	0.3798
13	0.423	0.381	0.404	0.3720	0.3160	0.4022
14	0.423	0.381	0.404	0.3720	0.3160	0.4022
15	0.310	0.344	0.329	0.3720	0.3099	0.3148
16	0.310	0.344	0.329	0.3720	0.3099	0.3148
17	0.251	0.251	**0.187**	0.3434	0.2500	0.2287
18	0.251	0.251	0.187	0.5212	0.2187	0.1667
19	0.580	0.563	0.691	0.5894	0.7200	0.6874
20	0.580	0.563	0.691	0.4988	0.5709	0.6353
21	0.355	0.382	0.374	0.2269	0.2371	0.2300
22	0.355	0.382	0.374	0.5996	**0.1910**	0.1663
23	0.395	0.334	0.361	0.4728	0.4871	0.6916
24	0.395	0.334	0.361	0.4094	0.4539	0.6385

From Table VII, it shows that, for uncoated, SVM prediction result has outperformed experimental data and regression by giving the Ra value of 0.1275µm, compared with 0.236µm and 0.226µm, respectively. For TiAlN coating, it was found that the SVM prediction result has outperformed experimental data and regression by giving the Ra value of 0.1910µm, compared with 0.232µm and 0.245µm, respectively. For SNTR coating, it was found that the SVM prediction result also has outperformed experimental data and regression by giving the Ra value of 0.1372µm, compared with 0.19µm and 0.187µm, respectively. The graft of prediction result is illustrated in Fig. 5- Fig. 7.

Fig. 5 – Fig. 7 show the graphs of comparison of experimental data, regression and SVM prediction. The prediction results of SVM were then validated based on the statistical analysis using SPSS software to find the accuracy of each model. Table VIII shows input parameters with RMSE values for the best SVM models while Table IX shows the paired sample t-test for each coating types to compare the SVM prediction with experimental data.

It can be seen in Table IX that all pairs are positively correlated with pair of EXP_ SNTR and SVM_SNTR gives the highest correlation value, 0.9682. A good prediction result will give a higher correlation value for each pair. A higher correlation value means that two sets of data are relatively similar to each other. Table X summarizes the result of most minimum Ra values for each coating tool for experimental data, regression and SVM models.

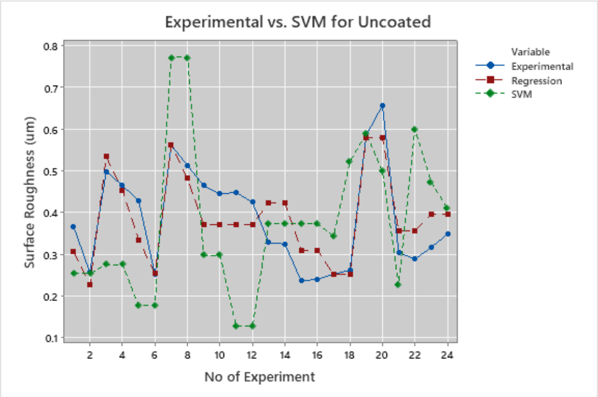

Fig. 5. Experimental vs. SVM for uncoated.

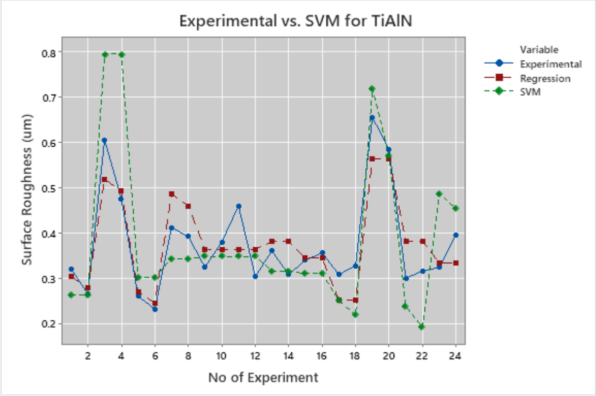

Fig. 6. Experimental vs. SVM for TiAlN.

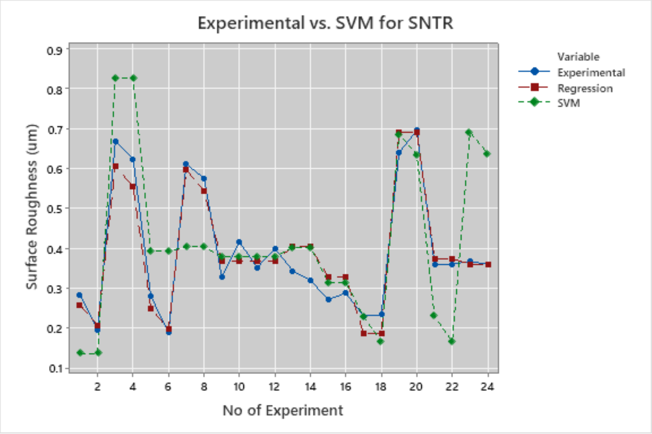

Fig. 7. Experimental vs. SVM for SNTR.

TABLE VIII. INPUT PARAMETERS AND RMSE VALUES FOR THE BEST SVM MODEL

Coating	C	Gamma	No. of support vector	RMSE
Uncoated	100	0.4	78	0.0739
TiAlN	100	0.333	34	0.0650
SNTR	1	0.333	20	0.0634

TABLE IX. PAIRED SAMPLE T-TEST

Paired Sample T-Test						
Pairs	Mean	Standard Deviation	Standard Error Mean	95% Confidence Interval		Correlation
				Lower	Upper	
EXP_UNC and SVM_UNC	0.0128	0.1846	0.0378	-0.0653	0.0904	0.9485
EXP_TIAN and SVM_TIAN	-0.0072	0.1031	0.0210	-0.0508	0.0363	0.9468
EXP_ SNTR and SVM_SNTR	-0.0218	0.1433	0.0292	-0.0823	0.0388	0.9682

TABLE X. MINIMUM RA VALUES IN END MILLING FOR EACH APPROACH

Approach	Uncoated (µm)	TiAlN (µm)	SNTR (µm)
Experimental	0.236	0.232	0.190
Regression	0.226	0.245	0.187
SVM	0.127	0.191	0.133

From Table X, it is shown that SVM model has outperformed experimental and regression model for uncoated, TiAlN and SNTR cutting tools in terms of minimum value of Ra. The minimum Ra has reduced for both regression and SVM about 1.57% and 33.05% respectively. Overall, it could be concluded that SVM is effective to predict the most minimum Ra value of end milling machining process.

IV. CONCLUSIONS

This study utilized the computational approaches method, Taguchi and SVM for modeling and optimization of surface roughness value in one of the traditional machining process, which is end milling. Three types of cutting tools were used to obtain the experimental data that are uncoated carbide WC-Co, common PVD-TiAlN and Supernitride (SNTR) coating. The significant parameters affecting the end milling performance, surface roughness values were obtained using the S/N ratio of the Taguchi method. From the study, it was found that:

1) Input parameter feed rate is the most significant factor affecting surface roughness value for all types of cutting tools.

2) The optimal level for uncoated end milling is where the input parameter cutting speed at level 1.4142 with 167.03 m/min, and input parameter feed rate at level -1.4142 with 0.025 mm/tooth and input parameter radial rake angle at level 0 with 9.5°.

3) The optimal level for TiAlN is where the input parameter cutting speed is at level 1 with 160 m/min, input parameter feed rate at level -1 with 0.03 mm/tooth and input parameter radial rake angle at level -1.4142 with 14.8°.

4) The optimal level for SNTR is where the input parameter cutting speed is at level 1.4142 with 167.03 m/min, the input parameter feed rate at level -1.4142 with 0.025 mm/tooth and the input parameter radial rake angle at level 0 with 9.5°.

5) For the end milling prediction, it has been found that SVM gives better prediction results compared with regression and experimental data for all three types of cutting tools.

6) Within these three cutting tools, uncoated cutting tools give the most minimum Ra which is 0.127µm compared to TiAlN and SNTR, 1.9µm and 1.32µm, respectively. Hence, it can be concluded that the uncoated cutting tool is the best cutting tool amongst the three types of cutting tools that are widely used in traditional machining process, especially end milling.

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Image Retrieval Evaluation Metric for Songket Motif

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Abstract*—Songket is a fine art heritage specializing in promoting the unique features of Malay identity. Past studies have shown that hundreds of Songket motifs had been produced, but unfortunately, most were not stored digitally. However, the digital collection of image data and determining its ground truth data should be given attention. This paper focuses on an evaluation metric to retrieve image Songket motifs. The initial label for each class of images in the database is ground truth data. The activity of determining the ground truth data involves two research objectives that have been discussed, namely identifying the ground truth data set of Songket Motifs involving Activity One, to obtain two ground truth data sets, precisely the training data set and the test data set involving six categories, to be specific 'Flora', 'Fauna', 'Nature', 'Cosmos', 'Food' and 'Calligraphy'. This phase test was carried out through a survey using a qualitative method, which is participatory by 15 respondents who have classified 413 specific motif images into 56 Songket motifs categories that refer to the six prominent motifs. Meanwhile, Activity Two is a validation-classification test of ground truth data sets by three experts to equate the selection of general and expert respondents to obtain training data sets for testing purposes involving six categories. After rearranging, only 50 ground truth Specific Motifs have been selected. Accordingly, the relationship coefficient correlation method is also implemented to see the relationship between two data through a statistical evaluation angle. In addition, precision and recall methods are also used to obtain precision and recall values for each ground truth data, and the F-measurement method is used to make a single evaluation. The F-measurement result for each category 'Flora': 26.7 – 100 (20 ID-Category), 'Fauna': 35.3 – 100 (6 ID-Category), 'Nature': 30.8 – 100 (5 ID-Category), 'Cosmos': 53.3 – 100 (7 ID-Category), and 'Motif': 47.6 – 100 (9 ID-Category). Using ground truth data enables image retrieval research to conduct unbiased system testing and evaluation.

***Keywords*—Heritage; songket motifs; songket motifs retrieval; ground truth data**

I. Introduction

Malaysia has a rich cultural and artistic heritage that can be divided into two categories: tangible cultural heritage and intangible cultural heritage. Tangible cultural heritage refers to physical objects that can be seen and touched, such as tombs and tombstones. On the other hand, intangible cultural heritage is based on knowledge and expertise that is passed down through oral traditions, cultural values, language, literature, and textiles, such as the traditional Songket [1]. Researchers have explored the use of the Content-Based Image Retrieval (CBIR) technique to study the Songket in intangible cultural heritage. Some of the research focuses on determining the basic geometric structure [2], decomposing the Songket Motif texture to match motif similarity [3], and refining the boundaries of Songket Motif images using canny edge detection techniques [4].

The study conducted by [2] and [3] focuses on the image retrieval model, which includes three main stages: pre-processing, processing, and post-processing. In this model, the pre-processing stage is particularly important as it involves the preparation of datasets, whether they are original or synthetic. Obtaining original data is a more challenging task as it requires the collection of images using a camera lens and converting them into digital format through editing. Therefore, researchers must put in extra effort to locate individuals or groups who actively use the data, such as Songket entrepreneurs and researchers.

According to the viewpoint put forth by [5], most of the information regarding Songket is still reliant on traditional methods, such as documentation and bookkeeping. Therefore, to conduct this study, it is imperative to undertake measures to digitize the information related to Songket. In the meantime, synthetic data can be obtained by downloading it from websites or producing it oneself, such as through paintings or anime, among others [6].

The image pre-processing stage involves two main parts: the determination of the ground truth data and the development of the image segmentation system [7]. Ground truth data is a set of master images that represent each image class in the database [8]. Determining the ground truth data helps in testing the image retrieval system more effectively. This process is carried out either based on human observation or by the system itself [9, 10]. The initial label for each class of images in the database is the ground truth data [8]. The use of ground truth data enables unbiased system testing and evaluation in image retrieval research [9]. Ground truth data can be established either by the system or through human observation [2, 3].

The image pre-processing stage was a significant focus of the study when Songket Motif's image retrieval model was introduced in references [2] and [3]. Image pre-processing involves determining the ground truth data and image segmentation. However, the determination of Songket Motif's ground truth data has not received enough attention, and most researchers perform testing by randomly selecting the Songket Motif. The goal of determining the ground truth data is to help in the fair processing of the image retrieval system's searching and browsing functionality.

The following text discusses the concept of ground truth data sets in research and their importance in producing accurate results. Specifically, the paper aims to determine ground truth data sets for Songket Motifs. To achieve this goal, both qualitative and quantitative methodologies are employed. Earlier studies, including [3, 8, 2], have also identified ground truth data sets for their research. However, this paper focuses solely on the Songket Motifs and their ground truth data sets. It is worth noting that the ground truth data set is a collection of data that has been established as authentic by either the user or the system. Its purpose is to ensure that the results obtained are reliable and trustworthy.

This paper is divided into five sections. The first section is an introduction and overview that discusses ground truth data determination along with any issues, objectives, and research methodologies. In the literature review section, key points from the literature are covered in detail and with a critical discussion. The third section focuses on the research methodology used to gather precise information about Songket Motifs. The fourth section deals with selecting experts and general users for the research. The fifth section contains the results and discussion, and the conclusion and acknowledgment follow afterward.

II. Literature Review

The main images in computer vision typically serve as a group representation for each image. They contain ground truth data, which is meant to show the essential components of each object in the image collection [9]. The primary label outlines the critical component of the object and its location in the image. As stated in [13], humans or systems must decide how to classify objects. Some commonly asked questions regarding identifying ground truth data include:

1) How ground truth data has been detected?

2) If using the system, is the first image ground truth data?

3) How has the system detected ground truth data?

4) If humans have detected ground truth data? What is the characteristic of expertise to be able to confirm it?

A study conducted by [9] utilized 80 general and eight expert participants to gather ground data based on human perception. The general participants were asked to identify relevant and commonly used English labels while searching and browsing landscape drawings. Meanwhile, the expert participants were tasked to provide the appropriate keyword for the ground truth data that could accurately describe each color notion evaluated in the landscape painting.

Furthermore, according to [10], establishing ground truth data by human observation is a challenging endeavor that takes much time. Different definitions and meanings exist of human perception and response to an object in an image [9]. To ensure that the ground truth data used is balanced to represent each category of variable data, however, human observation and the ability to determine the ground truth data are necessary [12].

Accordingly, geometrical data faces issues describing complex data structures and is even challenging to detail geometrically by natural data systems [10]. Thus, human observation of the shape structure is found to help facilitate the process of determining the ground truth data. In addition, the process of determining ground truth data can also determine the selection of labels or words of ground truth data required to implement tests at the testing stage of the proposed model and system [14]. This aims to enable the implementation of the evaluation and comparison of image retrieval results to take place somewhat and equitably for testing the image retrieval system.

III. Method

This phase involves two levels of activity. Activity One aims to identify the ground truth data set of Songket Motifs. Meanwhile, Activity Two is a ground truth data set classification process involving Songket Motif's images.

A. Identify Songket Motif's Ground Truth Data Set

This activity takes the form of a participatory test to determine the Songket Motif's data set in obtaining the ground truth data set, which is a participatory survey of human observation of form, where respondents must classify 413 images into six Songket Motif's categories, namely 'Flora', 'Fauna', 'Nature', 'Cosmos', 'Food' and 'Calligraphy'.

The respondents consisted of 15 users from two different backgrounds; Culture (directly involved in Songket research) and Information Technology. Respondents from the Cultural field are needed because they are more adept at identifying the structure of the ground truth data involving Songket Motifs. Meanwhile, respondents in the Information Technology field are more sensitive to the similarity of the shapes they see. Table I shows the background of the respondents.

TABLE I. Background of the Respondents

Occupations	Gender	Field
Student (1)	Female (8)	Culture (Songket Weaving) (11)
Work (14)	Male (7)	Information Technology (4)

Respondents were selected based on their knowledge of the form and motifs of Songket to conduct the test. Eight out of 15 respondents (53.3%) were female, while seven (46.6%) were male. All respondents were between 25 and 60 years old. The study aims to obtain a collective initial result to continue the system testing by classifying Songket Motif's data sets to ground truth data sets.

1) Research activity design: Based on Table II, this section is a further detail involving two Activities.

TABLE II. Aim and Method

Label	Research	Aim	Method
Activity One	Identifying the ground truth data set of Songket Motif's	Gets two sets of ground truth data, namely the set training data and test data involving six Songket Motif's categories ('Flora', 'Fauna', 'Nature', 'Cosmos', 'Food', and 'Calligraphy')	Qualitative method survey: Participatory. 15 respondents categorized 413 images involving six Songket Motif categories
Activity Two	Validation of ground truth data set classification	Validating a training data set for testing and evaluation purposes involves five categories ('Flora', 'Fauna', 'Nature', 'Cosmos', and 'Motifs')	Validation and use of training data sets (50 Songket Motif's). Comparison of F-measurement for five categories.

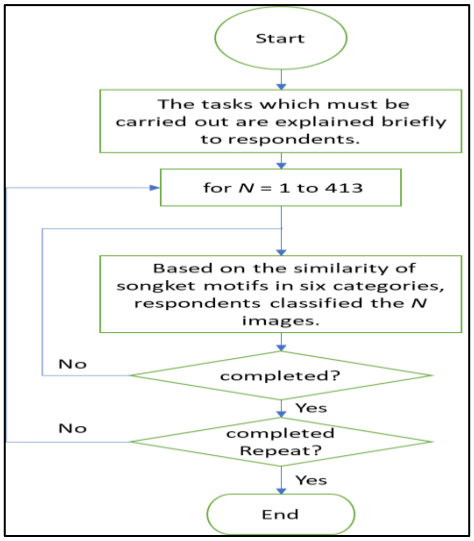

Start
The tasks which must be carried out are explained briefly to respondents.
for *N* = 1 to 413
Based on the similarity of songket motifs in six categories, respondents classified the *N* images.
No
completed?
Yes
No
completed Repeat?
Yes
End

Fig. 1. Flow chart of activities identifying the ground truth data set of Songket Motif's.

Identifying the ground truth data set of Songket Motifs refers to the flow chart displayed in Fig. 1. Each respondent was given a brief description of the task that needed to be carried out. After that, respondents were required to classify 413 Songket Motif images into six Songket Motif categories.

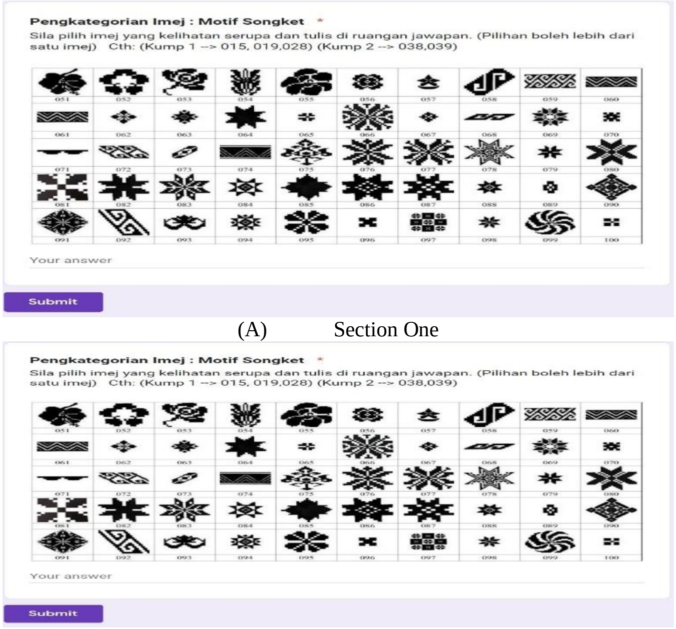
Activities are conducted using the same computer for each respondent in each session under the researcher's supervision. This aims to make it easier for respondents if there are questions on unclear matters. The specific Motif's image sizes are varied, and all specific motifs are labeled in numerical order from 001 to 413.

Respondents were free to choose shapes that were considered similar from a selection of specific Motif's image categories. Respondents must provide feedback for each page before the system allows the display of the next screen. This aims to ensure respondents provide feedback for all screen displays of the questions.

The test results show that the respondent's time to classify the similarity of 413 specific Motif images was more than 60 minutes, and the respondent's concentration decreased over time. Therefore, the number of specific Motif images was reduced to 200, and this test was divided into two sessions to ensure that the respondent's focus could be maintained as well as possible to obtain valid results.

All responses from respondents are recorded directly into an online file. Updates to this file are done automatically whenever there is feedback from respondents.

Fig. 2 displays an example of a participatory survey question for the two earliest examples of specific Motifs for sections One and Two with image IDs labeled 001-100. Respondents must choose to match the similarity of images that are seen to have similar shapes. If the respondent does not provide feedback, the respondent cannot press the "Submit" button because each question is marked * as a "Required question." Respondents' choice of matching answers can exceed more than one image for each group.



Pengkategorian Imej : Motif Songket *

Sila pilih imej yang kelihatan serupa dan tulis di ruangan jawapan. (Pilihan boleh lebih dari satu imej) Cth: (Kump 1 --> 015, 019,028) (Kump 2 --> 038,039)

Your answer

(A) Section One

Pengkategorian Imej : Motif Songket *

Sila pilih imej yang kelihatan serupa dan tulis di ruangan jawapan. (Pilihan boleh lebih dari satu imej) Cth: (Kump 1 --> 015, 019,028) (Kump 2 --> 038,039)

Your answer

(B) Section Two

Fig. 2. An example of a participatory survey question on the classification of Songket Motif's.

2) Validation of classification of ground truth data sets: Validation technique activities are carried out to validate or cross-check the ground truth data set of Songket Motifs identified in the previous phase. Table III is the background of the respondents involved in verifying the ground truth data arrangement of Songket Motifs according to different categories. The respondents consisted of three experts in the field of Culture (studying Songket and Batik) and Information Technology (conducting research involving image retrieval technology and Songket motifs), aged between 35 and 46 years. Because the respondents are experts, it is used as purposive sampling in Activity Two, that is, verification - classification of ground truth data sets.

This phase involves human evaluation of the appearance of specific motifs. The activities of this section are labeled as Activity Two and are carried out to achieve the objective of this study. Activity Two involved validation in identifying similar features of specific Motif shapes and evaluation of the confusion matrix. The two research questions for this phase are listed as follows to ensure that this activity achieves results.

TABLE III. RESPONDENT BACKGROUND

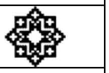
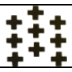
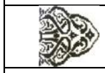
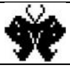
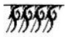
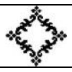
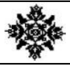
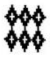
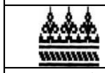
Respondent	Gender	Age	Field
Respondent #01	F	46 Years Old	Senior Lecturer in Information Technology & Songket
Respondent #02	F	37 Years Old	Lecturer in Heritage (Songket Researcher)
Respondent #03	F	35 Years Old	Researcher (Information Technology & Songket)

1) Is there a difference in the observation of specific Motifs between expert users and general users?

2) What are the results of the validation?

a) Validation test design – songket Motif’s classification: Songket motifs that general respondents have classified are 56 specific Songket motifs rearranged as in Table IV.

TABLE IV. SPECIFIC MOTIFS THAT THE GENERAL RESPONDENT HAS REARRANGED

Biji Tamar	Cermai	Nanas	Nona	Buah Delima
				
Cendawan	Pucuk	Pucuk Rebung	Sulur Kacang	Bunga Bintang
Bunga Bebaling	Bunga Ros Meletak	Kembang Semangkuk	Kemunting Cina	Melur
Pecah Empat	Tampuk Kecupu	Tampuk Kesemak	Tampuk Manggis	Tanjung
				
Bunga Kekwa	Bunga Flora	Bunga Kemuncup	Daun	Daun Keladi
				
Daun Lalang	Cengkeh	Peria	Burung Merak	Kupu-kupu
				
Siku Keluang	Gigi Yu	Rantai Unduk Laut	Unduk Laut	Sinar Matahari
Sirik	Bogan	Bunga Mahkota	Bunga Mangga	Pecah Lapan
				
Bunga Tudung Saji	Petak Catur	Pitis	Semangat	Mahkota Raja
Keris	Cabit	Awan Larat	Kendik Tali	Ombak
				
Kaligrafi	Madu Manis	Potong Wajik	Tepung Talam	Seri Kaya
				
Motif				

The results of the selection of general respondents have been rearranged and make the total number of Songket Motif’s used 413 involving 56 specific Songket Motif's, and each has been classified similarly to 413 specific Motif, and the number of specific motifs classified is between two to 52 specific Songket Motif’s images.

All specific Motif are printed on A4 size paper, and the size measurement for each specific Motif’s image is 2.7cm, intended to help expert respondents see each specific Motif’s image well. Meanwhile, activities are done individually in the same or different rooms. Before undergoing Activity Two, respondent information such as name, age, and gender is recorded. Then, the purpose of Activity Two and what the respondent needs to do are explained to the respondent. After the description related to the task was clarified, the expert respondents were shown 56 images of specific motifs, and the classification results that the general respondents had carried out are shown in Fig. 3.

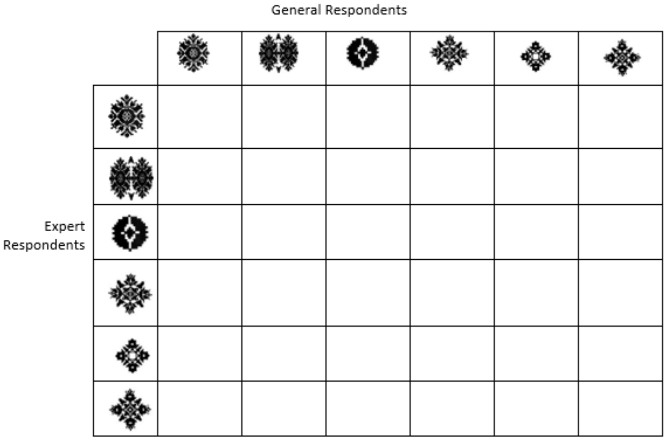
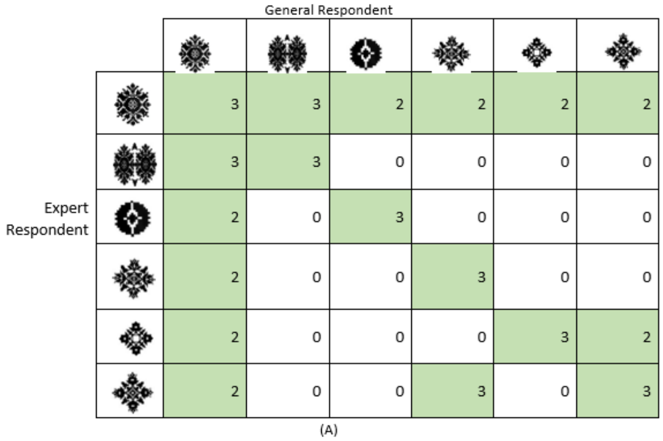


Fig. 3. Examples of specific Motif’s image categories and classification results that general respondents have implemented.

After expert respondents carry out the reclassification test, the ground truth data classification of the Songket Motifs is evaluated by calculating the confusion matrix formula, that is, using the technique formula of precision, recall, and F-measurement. The result of the selection of general respondents is the image in the database and all images achieved. Meanwhile, the selection of expert respondents is a relevant image. Accordingly, Fig. 4 shows that the column marked with the number two or three is a Songket Motif considered relevant by expert respondents. At the same time, the space marked with a blank (0) is a Songket Motif that is considered irrelevant. In Fig. 4(A), there are expert respondents (actual class) and general respondents (predicted class).

Next, Fig. 4(B) refers to the specific motifs in the first column displaying the highest F-measurement value, while the F-measurement value for the other specific Motif is lower. Therefore, for the specific Motif of 'Kembang Semangkuk' only one specific motif was selected as the ground truth data of the Songket Motifs for testing purposes.

A detailed description of this section is explained in the next section, which is the section on verifying the ground truth data analysis, and precisely in the next section.



3	3	2	2	2	2
3	3	0	0	0	0
2	0	3	0	0	0
2	0	0	3	0	0
2	0	0	0	3	2
2	0	0	3	0	3

Total	Precision %	Recall %	F Measurement %
6	100	100	100
2	33.3	100	50
2	33.3	100	50.
2	28.6	100	44.4
3	50	100	66.7
3	50	100	66.7

(B)

Fig. 4. Evaluation of the confusion matrix for the ground truth data Songket Motif's class 'Kembang Semangkuk' (A) Mark the confusion matrix (B) Calculation.

IV. Results and Discussion

Through the reclassification activity of ground truth data selection by expert respondents, 364 (88.14%) Songket Motifs were classified into 50 categories. The 50 classified categories refer to the structural similarity of specific motifs considered relevant by respondents. At the same time, another 49 (11.9%) motifs could not be classified because there was no matching of similar characteristics for different Motifs the respondent could implement. This is because the specific motifs stand alone, for example, the specific Motif 'Ayam Jantan', although there are other specific motifs that can be classified in the same class (birds), namely the specific Motif 'Itik Serati'. However, the similarity of the specific motifs is seen as the difference is too far. Therefore, such images cannot be considered in the same class. Table V. shows the name and amount for each specific Motif reclassified through expert respondent verification and confusion matrix evaluation. The results of this evaluation show that 50 categories of ground truth Songket Motif's data were obtained.

The ground truth data analysis process of Songket motifs was carried out after the participatory survey was completed; 56 categories of Songket Motifs classified by general respondents were rearranged by expert respondents into 50 categories of actual Songket Motifs data. This is because general respondents randomly arranged each specific Motif into 56 categories. Meantime, the expert respondents rearranged the motives based on the appropriateness of the actual structure of the Motifs according to the category. Therefore, the critical analysis required for this activity is the frequency distribution of 50 similar appearance categories for each of 413 specific Motifs and the percentage of agreement between respondents who agree to set a similar appearance for each specific Motif. Table VI is an example of the frequency distribution for 20 Songket Motif images taken from the test involving the first and last 10 results.

The Songket Motifs involved are the first ten Songket Motifs labeled ID-Image between 001 to 010 and the last 10 Songket Motifs labeled ID-Image between 404 to 413. ID-Image represents the identification of each specific Motif in the database. In contrast, the ID-Category represents the identification of the identity of each image of the ground truth data of the Songket Motifs that has been determined. Based on the frequency distribution, some information can be deciphered, such as ID-Image 002, categorized as a similar match for ID-Category 001 by 15 respondents. While referring to ID-Image 412-413, eight respondents stated that it was similar to ID-Category 013. This test found that the higher the number of respondents who made a mark, the more similar a form of ID-Category was to the marked ID-Image.

TABLE V. A Group of Songket motifs that Expert Respondents have Classified

Bil	Motif's	Total		Bil	Motif's	Total
001	Anggur	8		026	Motif	6
002	Awan Larat	5		027	Motif	5
003	Bunga Bintang	12		028	Motif	8
004	Bunga Bintang	11		029	Motif	9
005	Bogan	5		030	Motif	8
006	Cabit	6		031	Patah	3
007	Cengkeh	15		032	Pecah Empat	4
008	Cengkeh	9		033	Pecah Empat	5
009	Cengkeh	19		034	Pecah Empat	5
010	Cengkeh	10		035	Pagar	3
011	Cengkeh	8		036	Peria	8
012	Daun	7		037	Pitis	3
013	Kepala Lalat	10		038	Rantai Pecah Lapan	8
014	Motif	9		039	Pucuk Rebung Gigi Yu	10
015	Motif	7		040	Rantai Unduk Laut	6
016	Pergunungan	4		041	Semangat	9
017	Pergunungan	6		042	Siku Keluang	3
018	Pergunungan	5		043	Siku Keluang	11
019	Kembang semangkuk	6		044	Sinar Matahari	6
020	Keris	2		045	Kendik Tali	4
021	Melur	11		046	Kendik Sirik	5
022	Melur	16		047	Tanjung	7
023	Motif	2		048	Tanjung	7
024	Motif	3		049	Kendik Tali	8
025	Melur	7		050	Unduk Laut	10

TABLE VI. FREQUENCY DISTRIBUTION OF RESPONDENTS ACCORDING TO ID-IMAGE AND ID-CATEGORY FOR THE FIRST 10 SONGKET MOTIFS (ID-IMAGE 001-010) AND THE LAST 10 SONGKET MOTIFS (ID-IMAGE 404-413)

ID-Image ID-Category	001	002	003	004	005	006	007	008	009	010		404	405	406	407	408	409	410	411	412	413
001		15																			
002			15	15	15	15	15														
003																					
004																					
005										10							15				
006	10																				
007																		15			
008																					
009																					
010																					
011																					
012		15																			
013											... .									8	8
014																					
015																		15			
🟨	🟨	🟨	🟨	🟨	🟨	🟨	🟨	🟨	🟨	🟨		🟨	🟨	🟨	🟨	🟨	🟨	🟨	🟨	🟨	🟨
038																			15		
039												8	8	8							
040																			11		
041																					
042																					
043																					
044																					
045																				15	
046																					15
047																					
048																					
049																					
050																					

🟨 The respondent records no information for 20 ID-Image (016-037)

The minimum amount considered for the similarity percentage is eight respondents, equal to 53.3%, more than 50% of the respondents' agreement. The yellow column in Table VI refers to the ID-Category between 016 and 037, which means there is no matching information of specific Motif's image similarity done by the respondents for the ID-Category.

The highest frequency for each specific Motif shows the percentage of respondents who agree to classify the specific Motifs into a particular category. Some specific motifs get a higher or lower percentage of respondents' approval than others. Table VII shows the average value of the respondent's agreement evaluated through the results of the frequency distribution test, so the overall average value of the respondent's agreement amounts to 79.2%, categorized as ID-Category 001. However, the percentage of agreement of each ID-Category is different. For example, ID-Category 002, 020, and 037 have the highest agreement, 100%. All 15 respondents agreed that the specific Motif's match was similar. As for ID-image 041, the percentage of respondents' approval was only recorded at 63% for nine images, which is the lowest average value compared to other ID categories. The division of ID-Category 041 involves several parts, namely one image agreed upon by 15 respondents that is similar. In addition, two other images were agreed by 11 respondents that are like ID-Category 041. Simultaneously, there are six more Songket Motif images, with only eight respondents agreeing that they are similar, and the total number of respondents who agree is 85 out of 135. The number of similar images for ID-Category 041 is as many as nine specific motifs.

TABLE VII. SUMMARY OF THE AVERAGE VALUE OF THE RESPONDENTS' AGREEMENT EVALUATED THROUGH THE RESULTS OF THE FREQUENCY DISTRIBUTION TEST

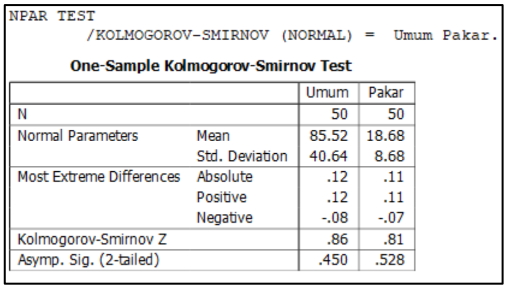
ID-Category	Similar Image Matches for each ID-Category	Total Number of Respondents Consent	Actual Total Mark	Average Value of Respondents' Agreement (%)
001	8	95	120	79.2 %
002	5	75	75	100 %
003	12	130	180	72.2 %
004	11	156	165	94.5 %
005	5	57	75	76 %
006	6	69	90	76.7 %
007	15	189	225	84 %
008	9	106	135	78.5 %
009	19	231	285	81 %
010	10	128	150	85.3 %
011	8	91	120	75.8 %
012	7	80	105	76.2 %
013	10	109	150	72.7 %
014	9	107	135	79.3 %
015	7	94	105	89.5 %
016	4	46	60	76.7 %
017	6	69	90	76.7 %
018	5	61	75	81.3 %
019	6	70	90	77.8 %
020	2	30	30	100 %
021	11	130	165	78.8 %
022	16	161	240	67.1 %
023	2	28	30	93.3 %
024	3	41	45	91 %
025	7	92	105	87.6 %
026	6	62	90	68.9 %
027	5	70	75	93.3 %
028	8	104	120	86.7 %
029	9	101	135	74.8 %
030	8	85	120	70.8 %
031	3	34	45	75.6 %
032	4	49	60	81.7 %
033	5	66	75	88 %
034	5	58	75	77.3 %
035	3	38	45	84.4 %
036	8	101	120	84.2 %
037	3	45	45	100 %
038	8	88	120	73.3 %
039	10	97	150	64.7 %
040	6	65	90	72.2 %
041	9	85	135	63 %
042	3	34	45	75.6 %
043	11	108	165	65.5 %
044	6	70	90	77.8 %
045	4	53	60	88.3 %
046	5	54	75	72 %
047	7	73	105	69.5 %
048	7	71	105	67.6 %
049	8	95	120	79 %
050	10	125	150	83.3 %

Accordingly, the correlation between general and expert respondents must be assessed using statistical methods. This aims to see the relationship between the two data that have been used.

A. *Correlation between the Selection of General Respondents and Expert Respondents*

To identify the relationship between the selection of general and expert respondents, the implementation of the relationship correlation test is one of the statistical methods often used [15]. The correlation test of the relationship coefficient using the 'Pearson Correlation method can be carried out, but it is necessary to go through a standard data determination test to see the P-Value *(Asymp. Sig(2 Tailed))* between the data of general respondents and expert respondents [16]. Accordingly, Table VIII shows the results of the selection of general respondents and expert respondents.

Based on Table VIII, the frequency distribution data test was carried out, and the results are displayed in Figure 5. According to [11], the P-value *(Asymp. Sig(2 Tailed))* obtained through the Kolmogorov Smirnov test needs to exceed 0.5% to enable the 'Pearson Correlation' method to be implemented. Thus, the evaluation results show that the data distribution for general and expert respondents is above 0.5%, which is general .450 and expert .528. Therefore, the results of the frequency distribution for this study are in a normal state. Therefore, the 'Pearson Correlation' method can be used for this study.



```
NPAR TEST
        /KOLMOGOROV-SMIRNOV (NORMAL) =  Umum Pakar.

        One-Sample Kolmogorov-Smirnov Test
                                             Umum    Pakar
N                                              50       50
Normal Parameters         Mean              85.52    18.68
                          Std. Deviation    40.64     8.68
Most Extreme Differences  Absolute            .12      .11
                          Positive            .12      .11
                          Negative           -.08     -.07
Kolmogorov-Smirnov Z                          .86      .81
Asymp. Sig. (2-tailed)                       .450     .528
```

Fig. 5. The test results used one sample Kolmogorov – Smirnov for the entire general election, and respondents showed a P-value exceeding 0.05%.

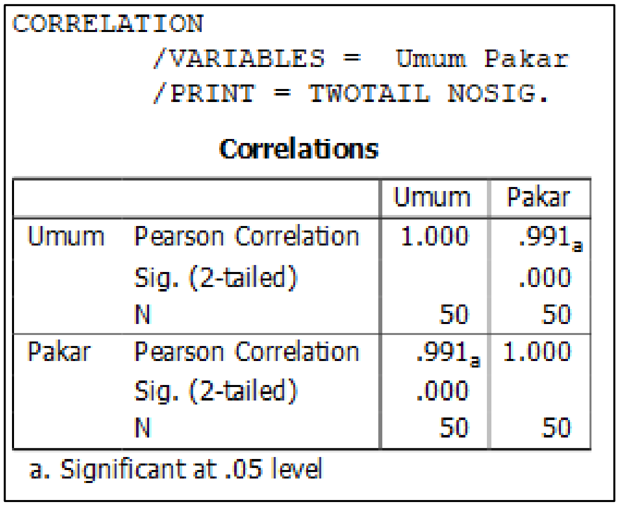
Referring to Fig. 5, the implementation of the relationship coefficient correlation evaluation has used the 'Pearson Correlation formula, which considers the correlation coefficient value *(r)*, the *N* value, the statistical *T* value, the *DF* value, and the *P* value. The *DF* value is the *'degree of freedom'* that indicates the number of independent values that can change in the analysis without violating any constraint 11]. Whereas the value of N is paired ranks' value the value of *N* I is required to calculate the statistical T formula. The T-Statistic formula is like1).

$$t = \frac{r * \sqrt{n-2}}{\sqrt{1-r^2}} \quad (1)$$

The correlation value of a good relationship should be between *-1 < r < +1* [12]. Accordingly, Fig. 6 shows the results of the evaluation that was carried out, obtaining a value of 0.991a. Thus, the results of the relationship coefficient correlation for this study show that there is a positive relationship coefficient correlation between general *(Umum)* respondents and expert *(Pakar)* respondents.

TABLE VIII. RESULTS OF THE SELECTION OF GENERAL AND EXPERT RESPONDENTS

ID-Category	General *(Umum)*	Expert *(Pakar)*
001	95	20
002	75	15
003	130	29
004	156	32
005	57	13
006	69	15
007	189	38
008	106	24
009	231	48
010	128	27
011	91	20
012	80	17
013	109	25
014	107	24
015	94	19
016	46	10
017	69	16
018	61	13
019	70	14
020	30	6
021	130	28
022	161	38
023	28	6
024	41	9
025	92	19
026	62	14
027	70	14
028	104	21
029	101	23
030	85	20
031	34	8
032	49	11
033	66	14
034	58	13
035	38	8
036	101	21
037	45	9
038	88	19
039	97	23
040	65	15
041	85	21
042	34	8
043	108	26
044	70	16
045	53	11
046	54	12
047	73	17
048	71	16
049	95	21
050	125	28



```
CORRELATION
        /VARIABLES =  Umum Pakar
        /PRINT = TWOTAIL NOSIG.
```

Correlations

		Umum	Pakar
Umum	Pearson Correlation	1.000	.991a
	Sig. (2-tailed)		.000
	N	50	50
Pakar	Pearson Correlation	.991a	1.000
	Sig. (2-tailed)	.000	
	N	50	50

a. Significant at .05 level

Fig. 6. The result of the Pearson Correlation value for general respondents is 1.00. while expert respondents are 0.991a.

Based on a comprehensive correlation coefficient test of fifty data between general and expert respondents, it was found that ID-Category 016, 018, 026, 035, 045, and 046 obtained the highest correlation coefficient result, which is one (1), the ID-Category representing specific Motif's 'Pergunungan1', 'Pergunungan2', ' Motif's ', 'Pagar', 'Kendik Tali', and 'Kendik Sirik'. Meanwhile, the other ID-Category obtained lower correlation coefficient results ranging from 0.65 to 0.95.

Furthermore, the ground truth data analysis part of the Songket Motif is a statistical information extract on matching similar images carried out by 15 general respondents and has been rearranged by expert respondents. After that, the similarity matching results were evaluated using confusion matrix analysis.

B. *Confusion Matrix Analysis of the Ground Truth Data of the Songket Motif's*

Songket motifs comprise six main categories: 'Flora', 'Fauna', 'Nature', 'Cosmos', 'Food', and 'Calligraphy' Motifs. Three prominent motifs have split motifs; the main motif 'Flora' is divided into six split motifs, namely 'Fruits', 'Trees', 'Flowers', 'Leaves', 'Spices', and 'Vegetables'. The main motif of the fauna is divided into two fractional motifs, namely 'Land' and 'Sea'. As for the main motif, 'Nature' is divided into two Motifs: ' Natural' and 'Things'. The main Motif of 'Cosmos' consists of three specific motifs; ' Awan Larat', 'Kendik Tali', and 'Ombak'; the total number of Songket Motif images for this category is 15 Songket Motif's images. However, the categories 'Food' and 'Calligraphy' were not chosen as the ground truth data of Songket Motifs because these motifs are rarely operated in any pattern commercially.

1) Songket Motif's category: The selection of Songket Motif's classification was done by respondents through the Activity One test, which identified the ground truth data set of Songket Motif. The re-determination of the ground truth data classification of Songket motifs by expert respondents was evaluated through a comprehensive confusion matrix calculation and is detailed in this section.

The confusion matrix technique's evaluation process is based on the criteria chosen by the respondents and categorized as images in the prediction class. Concurrently, images in the ground truth group of Songket Motifs are categorized as accurate class data. Once the confusion matrix evaluation table is completed, the matching process that the respondent has selected is carried out to enable the calculation process using the confusion matrix technique to be carried out. According to [9, 17], the advantage of the confusion matrix is that it can analyze the performance of each classifier in detail, even if the data set is unbalanced.

The performance measures often used are precision, recall, and F-measurement techniques. F-measurement evaluation is performed using True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) matrix values. The value of this matrix is evaluated for each class based on the obtained confusion matrix table [2, 13].

The definitions of TP, TN, FP, FN, precision, recall, and F-measurement are as follows:

TP: The number of accurate data correctly classified into its class by the classifier.

TN: Number of actual data classified into other classes by the classifier.

FP: The number of non-real data classified into its class by the classifier.

FN: Number of non-real data classified into other classes by the classifier.

Precision: The fraction of the number of accurate data classified exactly into its class divided by the total number of data classified in its class as in Eq. (2).

$$TP / (TP + FP) \tag{2}$$

Recall: The fraction of real data correctly classified into its class as in Eq. (3).

$$TP / (TP + FN) \tag{3}$$

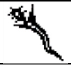
F-Measurement: The combination of precision and recall values produces a value called the harmonic mean to ensure that the measure of effectiveness correlates with precision. The F-measure formula is shown in Eq. (4),

$$F - Measurement = 2 * \frac{Precision * Recall}{Precision + Recall}$$

$$= \frac{2TP}{2TP+FP+FN} \tag{4}$$

Table IX shows the confusion matrix table involving the fractional motifs of 'Alam Benda', and the specific motifs of 'Keris'. Part A is a matching selection of respondent number three, representing three expert respondents in Part (A) who agree on the similarity of the specific Motif. When Part B results from a complete evaluation using the formula of precision, recall, and F-measurement.

TABLE IX. EVALUATION OF THE CONFUSION MATRIX FOR THE GROUND TRUTH DATA CLASS OF THE SONGKET MOTIF 'KERIS' PART (A) MARK THE CONFUSION MATRIX, PART (B) EVALUATION RESULTS FOR PRECISION, RECALL, AND F-MEASUREMENT

	3	3
	3	3

Total	Precision	Recall	F-Measurement
2	100	100	100
2	100	100	100

Next, Table X to Table XIV displays the performance evaluation results of the main motifs 'Flora', 'Fauna', 'Motif', 'Nature', and 'Cosmos' which involves 50 ground truth data of Songket Motifs that have been selected for the continuity of the image retrieval system testing process implemented in the testing and evaluation phase. Table X is the performance evaluation result of the 'Flora' ground truth Motif's image. The ID-Category involved is 004, 019, 036, 001, 012, 047, 031, 003, 022, 048, 033, 034, 032, 008, 021, 007, 025, 010, 009 and 011. Each obtained the result of calculating the F-measurement value between 26.7% to 100%.

TABLE X. RESULTS OF THE EVALUATION OF PERFORMANCE MEASUREMENT OF SONGKET MOTIF'S IMAGES IN THE 'FLORA' CATEGORY

Flora			
ID-Category	***Precision***	***Recall***	***F-Measurement***
004	100	100	100
019	100	100	100
036	100	100	100
001	72.7	100	84.2
012	63.6	100	77.8
047	61.5	100	76.2
031	60	100	75
003	52.2	100	68.6
022	50	100	66.7
048	46.2	100	63.2
033	45.5	100	62.5
034	45.5	100	62.5
032	36.4	100	53.4
008	36.5	100	53.5
021	31.3	100	47.6
007	25	100	40
025	21.9	100	35.9
010	19.2	100	32.3
009	17.3	100	29.5
011	15.4	100	26.7

Table XI shows the performance evaluation results of Songket Motif's images for the 'Fauna' category. Based on Table XI, six actual Songket Motif data are classified in the 'Fauna' category. The six ground truth data involve ID-Category 013, 043, 040, 039, 050, and 042. Meanwhile, the results of the F-measure evaluation are 100%, 92.3%, 92.3%, 89%, 72%, and 35.3%.

TABLE XI. RESULTS OF THE EVALUATION OF PERFORMANCE MEASUREMENT OF SONGKET MOTIF IMAGES IN THE 'FAUNA' CATEGORY

Fauna			
ID-Category	***Precision***	***Recall***	***F-Measurement***
013	100	100	100
043	85.7	100	92.3
040	85.7	100	92.3
039	80	100	89
050	56.3	100	72
042	21.4	100	35.3

Table XII. evaluates the performance measurement of specific Motif images for the 'Motif' category. This category is labeled as 'Motif' because specific Motif images obtained through different sources from [18], which is titled 'Symbolism in Terengganu Melayu songket motifs' and specific Motif in this class, cannot be mapped in any category that was introduced in the writing of the book. Therefore, in Table XII, nine ground truth Songket Motif's data are classified under the 'Motif' category. The nine ground truth data involve ID-Category 014, 015, 024, 029, 023, 026, 028, 030 and 027. Meanwhile, the results of the F-measurement evaluation are 100%, 100%, 75%, 58.1%, 57.1%, 54.5%, 53.3%, 53.3% and 47.6%.

TABLE XII. RESULTS OF THE EVALUATION OF PERFORMANCE MEASUREMENT OF SONGKET MOTIF'S IMAGES IN THE 'MOTIF' CATEGORY

Motif			
ID-Category	***Precision***	***Recall***	***F-Measurement***
014	100	100	100
015	100	100	100
024	60	100	75
029	40.9	100	58.1
023	40	100	57.1
026	37.5	100	54.5
028	36.4	100	53.3
030	36.4	100	53.3
027	31.3	100	47.6

Further, Table XIII shows the performance evaluation results of the ground truth Songket Motifs of the 'Nature' category. Referring to Table XIII, eight ground truth data of specific motifs are classified in the 'Nature' category. The eight ground truth data involve ID-Category 006, 020, 038, 046, 037, 005, 044, and 35. Meanwhile, the results of the F-measurement evaluation are 100%, 100%, 100%, 84.2%, 79.8%, 76.9 %, 63.2%, and 30.8%.

TABLE XIII. RESULTS OF THE EVALUATION OF PERFORMANCE MEASUREMENT OF SONGKET MOTIF'S IMAGES IN THE 'NATURE' CATEGORY

Nature			
ID-Category	*Precision*	*Recall*	*F-Measurement*
006	100	100	100
020	100	100	100
038	100	100	100
046	72.7	100	84.2
037	66.7	100	79.8
005	62.5	100	76.9
044	46.1	100	63.2
035	18.2	100	30.8

Table XIV is the ground truth data of Songket Motif's classified under the 'Cosmos' category. The seven ground truth data are ID-Category 002, 041, 045, 017, 049, 018, and 016. Meanwhile, the evaluation results of the F-measurement for ID-Category are 100%, 94.1%, 84.2%, 70.6%, and 70, respectively. %, 62.5%, and 53.3%.

TABLE XIV. RESULTS OF THE EVALUATION OF PERFORMANCE MEASUREMENT OF SONGKET MOTIF'S IMAGES IN THE 'COSMOS' CATEGORY

Cosmos			
ID-Category	*Precision*	*Recall*	*F-Measurement*
002	100	100	100
041	88.889	100	94.1
045	72.727	100	84.2
017	54.5	100	70.6
049	53.846	100	70
018	45.5	100	62.5
016	36.4	100	53.3

Referring to Table X to Table XIV, there is a low F-measurement value due to the calculation process using the confusion matrix technique; the selection for each category of similar Songket Motif types has the sum of several fractions of different Songket Motif types. For example, 'Daun' and 'Anggur' specific motifs were chosen by respondents as similar but in different categories. This is because the motif has a similar structure.

V. CONCLUSION

Two research objectives were discussed in determining the ground truth data for Songket Motif. The first objective was to identify the ground truth data set involving Activity One, which aimed to obtain two ground truth data sets: training data set and test data set. These data sets involved six categories: ' Flora', 'Fauna', 'Nature', 'Cosmos', 'Food', and 'Calligraphy'. The survey was conducted through a qualitative method involving 15 respondents who classified 413 specific motif images into 56 Songket Motif categories referring to the six prominent motifs.

The second objective was a validation-classification test of ground truth data sets by three experts. The aim was to equate the selection of general respondents with expert respondents to obtain training data sets for testing purposes involving six categories. After rearranging, only 50 ground truth Songket Motif's data were selected referring to five categories: 'Flora', 'Fauna', 'Nature', 'Cosmos', and 'Motif'. The relationship coefficient correlation method was implemented to evaluate the relationship between two data through a statistical evaluation angle.

In addition, precision and recall methods were also used to obtain precision and recall values for each ground truth data that had been selected. The F-measurement method was used to make a single evaluation that was the average value of each ground truth data. In Phase Two, the analysis of the study focused on human observation of the appearance of Songket Motifs.

VI. FUTURE WORK

The limitation of the study of determining ground truth data through human observation is that the detailed geometric characteristics are less effective because every human observation evaluates shape characteristics according to the individual's perception.

Thus, the technology determination technique is also able to help in the process of determining the ground truth data for the image retrieval research. Accordingly, this research can be developed by providing data determination techniques in computer vision.

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An Approach to Classifying X-Ray Images of Scoliosis and Spondylolisthesis Based on Fine-Tuned Xception Model

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***Abstract*—The vertebral column is a marvel of biological engineering and it considers a main part of the skeleton in vertebrate animals. In addition, it serves as the central axis of the human body comprising a series of interlocking vertebrae that provide structural support and flexibility. From basic works like bending and twisting to more complex actions such as walking and running, the spine's impact on human life is profound, underscoring its indispensable role in maintaining physical well-being and overall functionality. Moreover, in the hard-working schedule of people in modern life, a bunch of diseases impact on vertebral column such as spondylolisthesis and scoliosis. As a result, numerous researches were provided to take a hand in solving or avoiding these illnesses including machine learning. In this study, transfer learning and fine tuning were used for the classification of X-ray images on vertebrae sickness to avoid complex and wasted time in a medical examination process. The dataset for vertebrae illnesses X-ray images was collected at King Abdullah University Hospital and Jordan University of Science and Technology in Irbid, Jordan. It comprised 338 subjects including: 79 spondylolisthesis, 188 scoliosis, and 71 normal X-ray images. With the customized layers model in Xception that is used for image classification, we received surprisingly high results including validation accuracy, test accuracy, and F1 score in three-class classifications (i.e., spondylolisthesis, scoliosis, and normal) at 99.00%, 97.86%, and 97.86%, respectively. Additionally, two-class detection also received high accuracy values (i.e., 98.86% and 99.57%). Considering various high-performance metrics in the result indicates a robust ability to identify vertebrae diseases using X-ray images. The study found that machine learning significantly raises medical examinations compared to traditional methods, offering a myriad of benefits in terms of accuracy, efficiency, and diagnostic capabilities.**

***Keywords*—Transfer learning; fine tuning; spondylolisthesis; scoliosis; classification; Xception**

I. Introduction

In the busy world, many people deal with back problems like spondylolisthesis and scoliosis. These are issues with the spine that can make daily tasks such as working or studying harder. Spondylolisthesis happens when a vertebra in the spine moves out of place, causing pain in the lower back and sometimes putting pressure on nerves. Scoliosis is when the spine curves sideways in an unusual way. People with these conditions often have jobs that need a lot of physical effort, and sitting or standing for a long time can make things worse. To cope with these spine problems, many people use treatments that don't involve surgery. These include things like physical therapy, finding ways to manage pain, and making changes to the workspace to make it more comfortable. These steps help improve movement, reduce pain, and provide individuals continue contributing productively in their work.

Nevertheless, dealing with spondylolisthesis and scoliosis goes beyond just feeling uncomfortable. Moreover, it can also bring different levels of risk to people working even can be dangerous. If people do not take care of spondylolisthesis, it can lead to long-lasting pain, weak muscles, and even problems with nerves. Scoliosis, with its spine curvature, might cause breathing and heart issues and it affects overall health. In severe cases, surgery might be needed and make life more complicated. Despite these challenges, people should understand the management of their spinal conditions because it is crucial for motor nervous systems. In addition, it can help mitigate the risks associated with spondylolisthesis and scoliosis. This enables individuals to navigate their careers with resilience, adaptability, and a focus on their target.

Spinal diseases are increasing in modern times, especially scoliosis and spondylolisthesis. Despite this, symptoms of scoliosis with back pain are often overlooked by patients. In contrast, if people actively care about their health, we can easily identify the differences. Scoliosis and back pain seem to have specific characteristics in adult pain. For example, its location is often asymmetrical and associated with headaches. Furthermore, it is still unclear whether the intensity and duration of pain between adults with scoliosis and those without scoliosis experience back pain [1]. A lot of data collected in recent years around the world indicates the negative effects of scoliosis. To cite an example, the survey shows a dramatic rise in the average incidence of scoliosis diagnosis, climbing from 107 cases per 100,000 individuals in 2015 to 161 cases per 100,000 in 2022. Presently, approximately 1.2% of children and adolescents in Turkey are affected by scoliosis and the rate in women is 1.45 times higher than in men [2]. Besides, spondylolisthesis is a dangerous illness and it affects teenagers to elders. According to research degenerative lumbar spondylolisthesis affects 3% to 20% of globally and up to 30% of the elderly [3]. Additionally, research has shown that the illnesses are rare in those under 50 years old but they increase significantly with age affecting up to 15% of men and 50% of women aged 66–70 years [4]. This led to, people should pay more attention to their spine health to avoid future troubles.

X-ray images carry a pivotal role in the accurate diagnosis of spinal conditions, particularly in the classification of spondylolisthesis and scoliosis. X-ray images provide a comprehensive view of the spinal structure, enabling healthcare professionals to precisely identify and assess these conditions. However, X-ray imaging also has a bunch of limitations. Traditional methods rely heavily on manual interpretation, leading to the potential for human error and subjective variations in diagnosis. In addressing these challenges, machine learning emerges as a promising solution. By applying the power of artificial intelligence, machine learning algorithms can analyze vast datasets of x-ray images with high speed and accuracy. Nonetheless, it is crucial to acknowledge the limitations within the area of machine learning as well. The algorithms heavily depend on the quality and diversity of the training data, potentially leading to biased results. Furthermore, the interpretability of machine learning models in the medical field remains a challenge. Because of that, we need to improve machine learning models regularly to raise prediction and accuracy.

Artificial intelligence (AI) has come out as a trend in this day and age, particularly in the classification and segmentation of images. The ability of AI algorithms to categorize and organize huge datasets has transformed various industries [5], ranging from healthcare to finance. Machine learning techniques, such as deep learning and neural networks, have a main role in enhancing the accuracy and efficiency of classification tasks. These advancements have enabled AI systems to auto-recognize patterns, make predictions, and classify information with high precision. The integration of AI is also gaining prominence, addressing concerns about complex classification models such as illnesses on X-ray, MRI, and CT in health care [6]. In addition, if AI continues to develop its role will become unique in a new area where intelligent systems play an important role in decision-making processes across diverse domains. The trajectory of AI development in classification showcases its potential. This led to, we decided chose to develop the Xception model to gain high accuracy and solve more errors in X-ray image classification.

In this research, we use deep learning in the classification of images. In more detail, transfer learning was used to enhance performance in a novel task by utilizing knowledge acquired from previous learning experiences in similar tasks. By doing so, the model can capitalize on the generalized knowledge it has acquired, thereby improving its ability to tackle new challenges without starting from scratch [7]. Overall, transfer learning offers a powerful and efficient way to leverage previously acquired expertise, fostering improved performance and generalization across a range of tasks. In addition, fine-tuning is an important next step where the pre-trained model or its components are adjusted and optimized specifically for the new task [8]. This fine-tuning process ensures that the model adapts its learned features to the nuances of the target task, striking a balance between the general knowledge gained and the specifics of the current task. For this reason, we propose a method to use the Xception model in the Keras library in a Convolutional Neural Network (CNN) that uses transfer learning and fine-tuning to classify images. Once trained, our model can classify new images or extract features for use in other applications such as object detection or image segmentation.

The contributions of this paper are as follows:

- Our research gains a high accuracy including validation accuracy, test accuracy, and F1 score in three classes' classifications in spondylolisthesis, scoliosis, and normal spine at 99.00%, 97.86%, and 97.86%, respectively. Moreover, pair-wise classification also achieves a high success up to 99.57%.
- Our study suggests a complete model that is used for vertebrae X-ray image classification including a dataset of scoliosis, spondylolisthesis, and normal vertebrae X-ray images. Thus, an expert can apply it in a simple way to help with the detection and classification of X-ray images.
- We find that Partition Explainer can be used effectively which is an algorithm that uses a hierarchical clustering of the data to recursively partition the input space.
- Our collected X-ray images of subjects with scoliosis and spondylolisthesis, as well as healthy ones, as determined by the specialists in the hospital This dataset is confirmed for the development of a model in deep learning including transfer learning and fine-tuning for the classification of vertebrae and can be applied to training and educating medical students, residents, and experts.

Our study comprises four main sections. Section II illustrates some of the related research that we used for references. Section III is the methodology, this section makes clear in detail all of the methods used in the article. Following that, Section IV will outline the experiments, detailing the methodology employed for conducting and assessing the accuracy of the deep learning model. Finally, we will provide a summary of our article and scrutinize the fundamental domains connected to the study in Section V.

II. Related Work

An occupied working environment nowadays such as spending a lot of time at the working table or taking hours in the library to study. Based on several studies showing that, every year about 523 out of 100,000 teenagers develop scoliosis. This condition was twice as common in females compared to males based on the study population comprising 1782 teenagers from 10 to 18 years old [9]. Consequently, several researches on machine learning have been published for the segmentation and classification of X-ray images. For example, Peiji Chen et al. classified patient spine pictures using ResNet and Faster R-CNN. As a result, the combined use of ResNet convolutional neural network and Faster R-CNN has a stronger classification effect on scoliosis disorders than traditional machine learning approaches, as completely illustrated by the Area Under the Curve value of 90.87% [10]. Moreover, Joddat Fatima et al segmented the spinal column using Mask RCNN in conjunction with the YOLOv5 method for vertebral localization. The suggested method achieves 94.69% final average classification accuracy [11].

Machine learning plays a central role in classifying X-ray images for medical diagnosis. By leveraging algorithms, it can automatically identify patterns indicative of various conditions. This enhances diagnostic accuracy, expedites analysis, and contributes to more efficient and precise healthcare decision-making. Consequently, Shuman Han et al classified patients with moderate scoliosis with an accuracy of 77.9% and severe scoliosis with an accuracy of 93.6% using x-ray pictures of 204 patients with idiopathic scoliosis using the integrated area algorithm method of machine learning [12]. In addition, with a high accuracy of about 90.0%, Wahyu Caesarendra et al. suggest a deep learning architecture for the recognition of spine vertebrae from X-ray images [13]. This architecture automatically evaluates the Cobb angle and assesses for the presence of scoliosis and the severity of the curvature.

Especially in the analysis of X-ray pictures, Convolutional Neural Network (CNN) have completely changed deep learning for image classification. Their capacity is automatically extract hierarchical characteristics from pictures allows for the correct identification of patterns suggestive of different medical problems. CNN is required for improving X-ray image classification in medical diagnostics in terms of accuracy and precision. Furthermore, CNN is a common way to diagnose spondylolisthesis X-ray images in humans. For example, Fatih Varçın et al. used the MobileNet model in Convolutional Neural Network to classify spondylolisthesis or normal and achieved high results with a test accuracy reach of 99% [14]. Moreover, Deepika Saravagi et al. collected 229 X-ray images which include spondylolisthesis and the normal spine (i.e., 156 spondylolisthesis and 143 normal) which were optimized by applying the TFLite model optimization technique. As a result, the model reaches a high accuracy rate including the VGG16 model of 98% and InceptionV3 of 96% [15]. Additionally, Fatih Varçın et al. also AlexNet and GoogleLeNet models to classify the data set consisting of 272 X-ray images. According to experimental results, GoogleLeNet performs marginally better than AlexNet, which has an accuracy of 91.67%, with a 93.87% accuracy rate [16].

Processing medical images in X-ray images has witnessed significant promotions through the utilization of transfer learning and fine-tuning techniques. Leveraging pre-trained models allows the transfer of knowledge from general domains to medical imaging while fine-tuning tailors the model for specific diagnostic tasks. This approach enhances the efficiency and effectiveness of X-ray image analysis in medical applications. For instance, Mohammad Fraiwan et al. used transfer learning in the DensNet-201 model and reached a mean accuracy and maximum accuracy for spine illness classification were 96.73% and 98.02%, respectively [17]. Furthermore, Using the VGG16 model for feature extraction and CapsNet for disease identification, Deepika Saravagi's experimental results show 98% accuracy [18]. The dataset contains 466 X-ray radiographs, with 186 images showing a spine with spondylolisthesis and 280 images showing a normal spine.

Deep learning models could help handle the growing amount of medical imaging data and offer an early analysis of pictures collected in basic care. When it comes to scoliosis identification, deep learning algorithms provide a faster and more effective solution than manual X-ray investigation. Arslan Amin et al. used a pre-trained EfficientNet model to achieve an accuracy of 86 % on the detection and classification of scoliosis from X-ray images [19]. Besides, Ariana Alejandra Andrews Interiano et al. take a database of medical images from Honduran to transfer learning and fine-tuning in InceptionResNet, MobileNet, and EfficientNet. Hence, their experiment finds a high average accuracy of 98.01% [20]. Furthermore, Dalwinder Singh et al. applied CNN to classify MRI lumbar spine images and used differential spider monkey optimization (SMO) to get the highest classification accuracy of 96% [22]. In conclusion, a bunch of different research has been published in recent times to propose the accuracy in segmentation and classification in medical and help patients avoid a lot of time and money for a long procedure in treatment.

III. Methodology

A. The Research Implementation Procedure

This study proposes a method including 12 steps shown in Fig. 1. The roles of the steps are shown as follows:

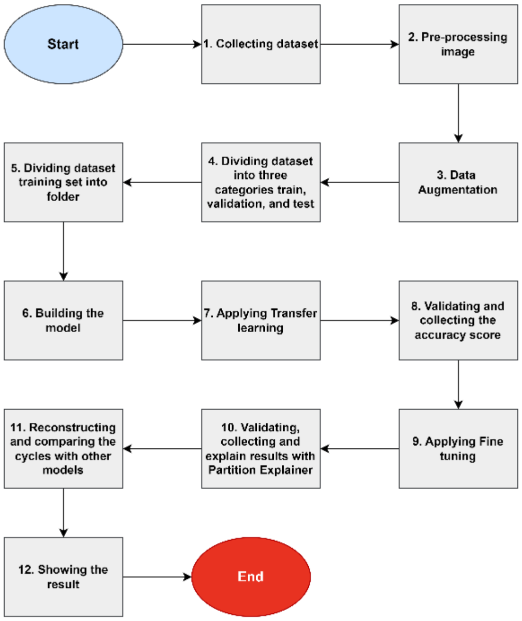
Start
1. Collecting dataset
2. Pre-processing image
3. Data Augmentation
4. Dividing dataset into three categories train, validation, and test
5. Dividing dataset training set into folder
6. Building the model
7. Applying Transfer learning
8. Validating and collecting the accuracy score
9. Applying Fine tuning
10. Validating, collecting and explain results with Partition Explainer
11. Reconstructing and comparing the cycles with other models
12. Showing the result
End

Fig. 1. The implementing procedure flowchart.

1) *Collecting dataset:* The dataset about vertebrae illnesses is collected at King Abdullah University Hospital and Jordan University of Science and Technology in Irbid, Jordan. The collection contains X-ray images of two types of spine illness that is spondylolisthesis, and scoliosis. Besides, one class for normal images is provided. This collection provides a valuable resource for medical research.

2) *Pre-processing image:* Standardized input conditions were fixed for CNN models through the use of resizing and normalization. As a result, the outcomes of the results grow.

3) *Data augmentation:* This step is a technique of artificially increasing the dataset by creating modified copies

of a dataset using existing data to apply functions such as rotate, flip, and brightness contrast.

4) Dividing the dataset into three categories train validation and test: The entire X-ray images dataset includes 3500 subjects after increasing in data augmentation by 338 default subjects with random selection used in the phases of training, validation, and testing. An 8-1-1 scale is used to randomly choose the datasets, dividing them into eight halves for training, 1 for validation, and 1 for testing. This ensures a balanced distribution, which is necessary for reliable model creation and assessment.

5) Dividing the training set into folders: spondylolisthesis, scoliosis, and normal spine are divided into many different folders. The first folder is 3-fold including spondylolisthesis, scoliosis, and normal spine. Our goal is to compare the largest folder by displaying the training data in a more precise manner. As a result, the other folder has 2-fold classifications: scoliosis-normal and spondylolisthesis-normal.

6) Building the model: To do experiments, we used transfer learning to a pre-trained model and rebuilt the model based on the CNN architecture prototype. Subsequently, fine-tuning is the process of modifying the weights of the pre-trained model on the particular data of the target job. Consequently, the Xception model produces an outstanding outcome for our training test.

7) Applying transfer learning: In transfer learning, a large dataset was used for leveraging a pre-trained model. This dataset may contain a large amount of labeled data. By using knowledge gained from the source task, transfer learning enhances the performance of the model on the target task, particularly when data for the latter is limited.

8) Validating and collecting the accuracy score: We summarized the training accuracy obtained from the predictions made by the model to evaluate its accuracy after it had finished training. Next, we used the initially divided testing set to assess whether the test was correct.

9) Applying Fine tuning: Fine-tuning was applied to the act of modifying the parameters of a pre-trained neural network and the hyperparameters of a model to improve its performance, often in the last layers. This enables the model to draw on elements learned in a broader context while customizing its knowledge to the specifics of the target task.

10)Validating, collecting and explain results with Partition Explainer: After collecting all the metrics such as validation accuracy, test accuracy, and F1 score. After that, a partition explainer in SHAP was used for a specific algorithm for explaining the output of machine learning models. SHAP is a unified approach to explaining the output of any machine learning model, and it is based on Shapley values from cooperative game theory.

11)Reconstructing and comparing the cycles with other models: After the first phase, we rework and compare it with another model including EfficientNetB3, VGG19, ResNet101, and DenseNet169 to create the final result.

12)Showing the result: Following a comparison, the data will be displayed in the form of tables and graphs to allow for relevant comparisons.

B. Pre-processing Image

In the area of image processing, the pre-processing stage plays a central role in enhancing the efficiency and effectiveness of subsequent tasks, such as machine learning model training. Two fundamental operations within this pre-processing pipeline are image resizing (1) and normalization (2). Image resizing involves transforming the dimensions of an image, commonly to a standardized size, to facilitate uniformity and computational feasibility.

The resizing operation is typically represented by the formula:

$$Resized\ Image = Resize\big(Original\ Image, (224{,}224)\big)\# \quad (1)$$

In Formula , the original image goes through a transformation to conform to a predefined resolution of 224×224 This standard size is often used to ensure consistency across the dataset and compatibility with neural network architectures commonly used in computer vision tasks.

Following resizing, the next critical step is normalization, see Formula (2), a process focused on normalizing the pixel values of the image. Normalization is carried out to ensure that the input data falls within a specific range, which aids in stabilizing the learning process during model training. The normalization operation can be mathematically expressed as:

$$Normalized\ Image = \frac{Resized\ Image - \min(Resized\ Image)}{\max(Resized\ Image) - \min(Resized\ Image)}\# \quad (2)$$

Here Formula (2), the pixel values of the resized image are transformed to a range between 0 and 1 by subtracting the minimum pixel value and dividing by the range between the maximum and minimum pixel values. This normalization to the [0, 1] range is crucial for mitigating issues related to varying scales and ensuring that the model receives consistent input across diverse images.

In summary, the connection of resizing and normalization in image pre-processing not only standardizes the size of input images but also establishes a common pixel value scale.

C. Data Augmentation

Augmenting data is a critical step in improving the robustness and generalization capability of machine learning models, notably in picture classification. One widely used strategy involves applying several changes to the original images, resulting in a diverse set of training samples for the model to learn from.

The first step in Formula (3) is the transpose operation involves swapping the rows and columns of the image matrix. Mathematically, if we have an image represented by a matrix I of dimensions $m \times n$, where m is the number of rows and n is the number of columns, the transpose has denoted as I_{trans} (3)

results in a new matrix with dimensions $n \times m$, it can be expressed as:

$$I_{trans} = I^{T} \# \tag{3}$$

The next step in Formula (4), shift scale rotate is used for translations, scaling, and rotations to the image. The rotated image I_{rot} is obtained by applying a rotation matrix $R(\theta)$ (4) to the original image matrix I:

$$I_{rot} = R(\theta) \cdot I \# \tag{4}$$

Here, the rotation limit is set to 45 degrees ($\theta \leq 45$) with a probability p = 0.45 for each image. This ensures a controlled augmentation process that is both effective and computationally efficient.

The third step , horizontal flip (5) and vertical flip (6) operations involve mirroring the image horizontally and vertically, respectively. By means of mathematics, the horizontal flip $I_{horizontal\_flip}$ (5) is achieved by reversing the order of columns in the original image matrix I, and the vertical flip $I_{\text{vertical\_flip}}$ (6) is achieved by reversing the order of rows:

$$I_{horizontal\_flip} = flip(I, axis = 1) \# \tag{5}$$

$$I_{\text{vertical\_flip}} = flip(I, axis = 0) \# \tag{6}$$

Both operations are applied with a probability of $p = 0.5$ to introduce variability in the orientation of the training samples.

The final step (7) is one operation of random brightness contrast and it can be expressed as a single formula, where the brightness and contrast adjustments are applied to each pixel in the image:

$$I_{bc} = I + r_{brightbess} \times I \times r_{contrast} \# \tag{7}$$

In this formula, I_{bc} (7) represents the image after the combined brightness and contrast adjustments, I is the original image matrix. Moreover, $r\_brightbess$ (7) is a randomly sampled value for brightness adjustment, and $r\_contrast$ (7) is a randomly sampled value for contrast adjustment.

These adjustments are executed with a probability of $p = 0.2$ to ensure controlled variability without excessively distorting the image characteristics. In summary, these augmentation techniques collectively contribute to a more diverse and robust dataset, fostering improved performance and generalization of machine learning models in image classification tasks.

D. Transfer Learning and Fine Tuning of Xception

Transfer learning and fine-tuning are powerful techniques in the area of CNN [22], [23], allowing the utilization of pre-trained models to enhance the performance of a specific task. One noteworthy architecture for such applications is the Xception model, which stands out for its depth and efficient use of parameters. Unlike traditional CNN, Xception uses an extreme version of the inception module, known as the depthwise separable convolution. This technique separates the spatial and channel-wise operations, enabling the model to capture both local and global features effectively.

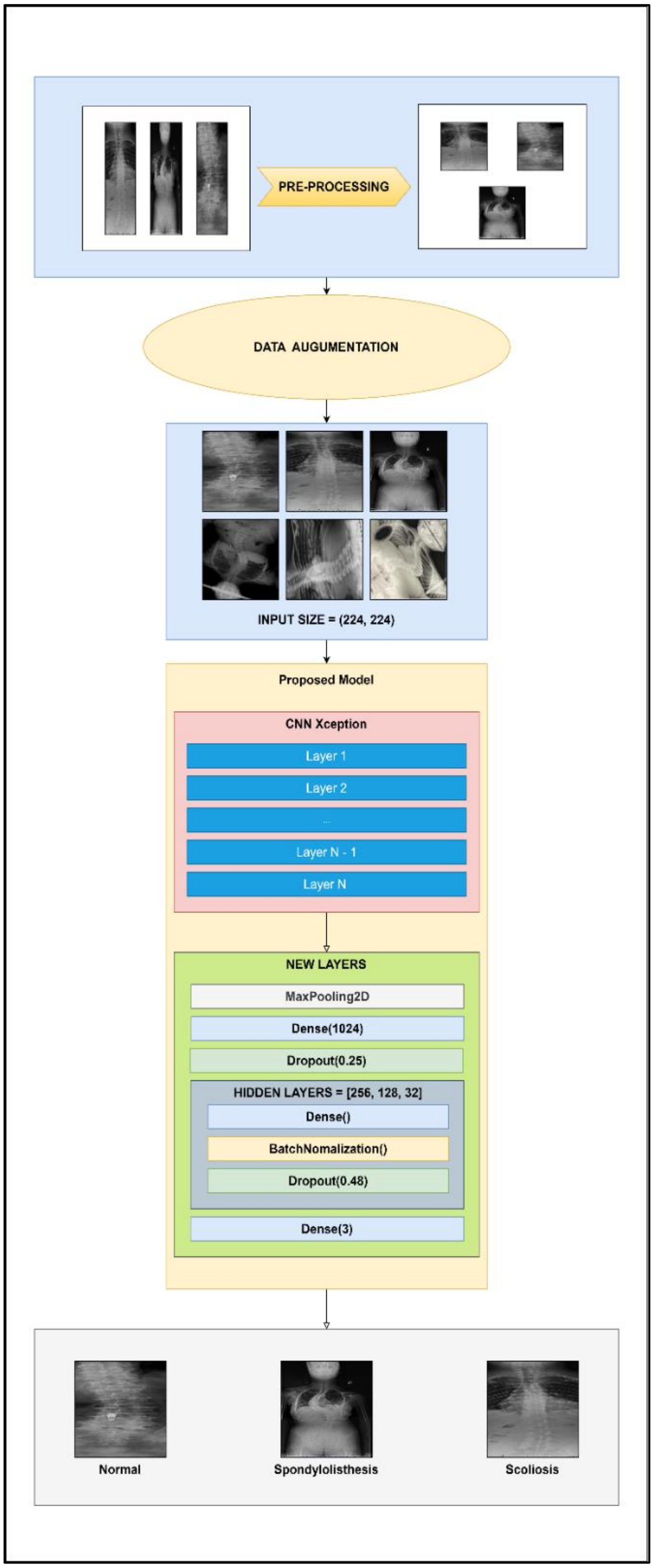

Fig. 2. Procedure of transfer learning and fine-tuning in CNN Xception model and custom layers.

The Xception model, introduced by François Chollet in 2017, is an extension of the Inception architecture. Its key innovation lies in replacing standard convolutions with depthwise separable convolutions, resulting in a more efficient and parameterized model. This architectural shift reduces the risk of overfitting, enhances feature representation, and facilitates faster training convergence. Each depthwise separable convolutional block in Xception consists of a depthwise convolution followed by a pointwise convolution, providing a powerful yet lightweight alternative to conventional convolutional layers.

When it comes to transfer learning and fine-tuning in CNNs, the Xception model proves particularly advantageous. Leveraging the pre-trained weights from a large dataset, such as ImageNet, Xception can be employed as a feature extractor for a diverse range of computer vision tasks. Our study adds more external layers to increase accuracy in Fig. 2 and this process not only saves computational resources but also leverages the rich hierarchical features learned by Xception, enhancing the model's ability to generalize across various visual patterns.

In essence, the seamless integration of the Xception model into CNN architectures and the addition layer described in Fig. 2 for transfer learning and fine-tuning extends the paradigm of leveraging pre-trained models, unlocking the potential for enhanced performance and efficiency in a myriad of computer vision applications.

E. Explain Results with Parition Explainer

In the study, Partition Explainer a method within SHAP (Shapley additive explanations) was chosen as a visual explanation. It serves as a necessary tool in explaining the contributions of individual features in an image-based model. This process is particularly useful for understanding the importance of different aspects within an image and gaining insights into model decision-making. At its core, the Partition Explainer leverages Shapley values, a concept rooted in cooperative game theory, to fairly distribute the model's output among its input features.

In more detail, the Partition Explainer operates by considering all possible subsets of features and calculates the average Shapley value (8) for each feature across these subsets. This careful approach ensures a comprehensive evaluation of the impact of each feature, accounting for their interactions and dependencies. Mathematically, the Shapley value for a feature (φ_i) (8) in a cooperative game is expressed as follows:

$$\varphi_i(f) = \sum_{S\subseteq N\setminus\{i\}} \frac{|S|\,!(|N|-|S|-1)!}{|N|!}\,[f(S\cup\{i\}) - f(S)]\,\# \quad (8)$$

In this Formula (8), N represents the set of all features, S denotes a subset of features excluding 'i', and f(S) signifies the model's output when considering the subset of features 'S'. The Shapley value quantifies the marginal contribution of feature 'i' by averaging across all possible combinations, providing a fair and consistent measure of its impact on the model's output.

In the context of the Partition explainer, this Shapley value calculation is extended to various feature subsets, enabling an expression understanding of how each feature influences the model's predictions.

By using Partition explainer in the final result of Fig. 3, our results gain insights into model behavior, fostering trust and facilitating informed decision-making in the area of machine learning.

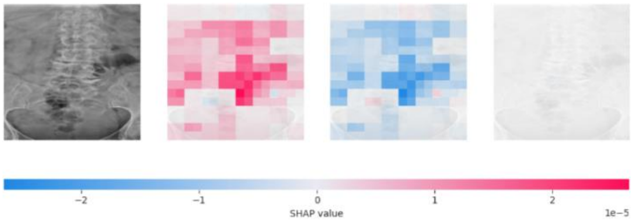

Fig. 3. The final result of classification spondylolisthesis after applying a partition explainer.

IV. Experiments

A. Dataset and Peformance Metrics

For this analysis, a single dataset Fig. 4 was used for training, validation, and testing. A total of 338 pictures, comprising 79 spondylolisthesis, 188 scoliosis, and 71 normal, make up the full X-ray images dataset that was obtained and enhanced by King Abdullah University Hospital and Jordan University of Science and Technology in Irbid, Jordan. The dataset increased to 3500 pictures after data augmentation and it was divided into 8 for training, 1 for validation, and 1 for testing.

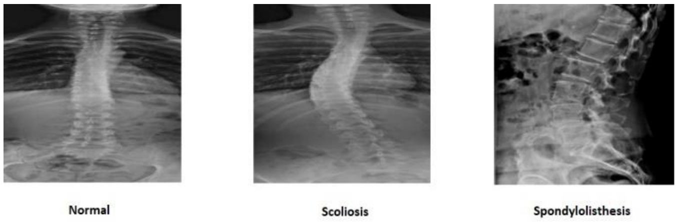

Fig. 4. Dataset about the vertebrae X-ray images.

Additionally, five measures were used to evaluate the model performance: the F1 score, test accuracy, recall, precision, and validation accuracy all have a significant impact on how well a trained model performs and its capacity for generalization.

The F1 score in Formula (9) is the harmonic mean of precision and recall. It balances the trade-off between precision and recall, providing a single value that takes both false positives and false negatives into account. The F1 score is calculated as follows:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}\,\# \qquad (9)$$

Test accuracy as in Formula (10) measures the proportion of correctly predicted instances over the total number of instances in the test set. It is a common metric for overall classification performance, providing insights into its real-world applicability. This metric is calculated by:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}\,\# \qquad (10)$$

Validation accuracy in Formula (10) is similar to test accuracy, it measures the proportion of correctly predicted instances over the total number of instances in the validation set. It is used during the training process to monitor the model's performance on a separate dataset not used for training.

Precision in Formula (11) talks about the accuracy of positive predictions made by the model, emphasizing minimizing false positives. The precision formula is given by:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}\# \qquad (11)$$

Recall in equation (12), a metric crucial in scenarios where identifying true positives is paramount, is defined as:

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}\# \qquad (12)$$

B. Scenario 1: The Results of Classifying X-Ray Images into Two Classes: Scoliosis and Normal Spine

Through customization and training, the scenario aimed to assess how well the pre-trained models performed in correctly diagnosing the X-ray image condition. Furthermore, by using these statistics, we may more easily and intuitively compare the vertebral X-ray images in three classes: normal spine, scoliosis, and spondylolisthesis.

Table I show the performance evaluation metrics for classifying in two classes. The ResNet101 achieved the highest accuracy value in transfer learning over the two statistical measures with a validation accuracy of 99.14%. Test accuracy, precision, and F1 score all reached 98.29%.

On the other hand, in Table II TABLE II. shows our model performed the best after fine-tuning with a validation accuracy of 98.86%. Test accuracy, precision, and F1 score all reached 99.14%. This led to, underscore the effectiveness of customizing the model to the nuances of the target task through fine-tuning. This suggests that while transfer learning provides a strong foundation, fine-tuning allows for a more tailored approach, particularly when dealing with domain-specific nuances.

A sample training and validation progress curve with the loss and accuracy values of our model during fine-tuning is displayed in Fig. 5 and Fig. 6. The graphic shows suitable training and validation sets along with consistent learning behavior. Thus, it shows how our work's fine-tuning accuracy has increased.

TABLE I. THE ACCURACY OF CLASSIFYING X-RAY IMAGES INTO TWO CLASSES: NORMAL SPINE AND SCOLIOSIS IN TRANSFER LEARNING, FOR EACH DEEP LEARNING MODEL

Model	Transfer learning				
	Val acc	Test acc	Precision	Recall	F1
EfficientNetB3	99.00%	97.71%	97.74%	97.71%	97.72%
DenseNet169	88.29%	87.43%	87.24%	87.43%	87.31%
VGG19	94.29%	80.14%	90.86%	90.86%	90.86%
ResNet101	99.14%	98.29%	98.29%	98.29%	98.29%
Our Model	**87.00%**	**83.86%**	**84.33%**	**83.86%**	**84.05%**

TABLE II. THE ACCURACY OF CLASSIFYING X-RAY IMAGES INTO TWO CLASSES: NORMAL SPINE AND SCOLIOSIS IN FINE TUNING, FOR EACH DEEP LEARNING MODEL

Model	Fine tuning				
	Val acc	Test acc	Precision	Recall	F1
EfficientNetB3	97.71%	97.43%	97.42%	97.43%	97.42%
DenseNet169	96.00%	94.00%	93.94%	94.00%	93.95%
VGG19	73.71%	73.57%	54.13%	73.57%	62.37%
ResNet101	79.57%	78.57%	77.09%	78.57%	75.90%
Our Model	**98.86%**	**99.14%**	**99.14%**	**99.14%**	**99.14%**

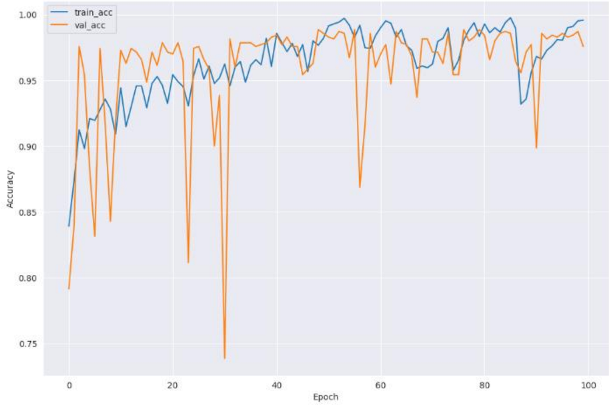

Fig. 5. Training accuracy and validation accuracy in fine-tuning in two classes normal and scoliosis of our model.

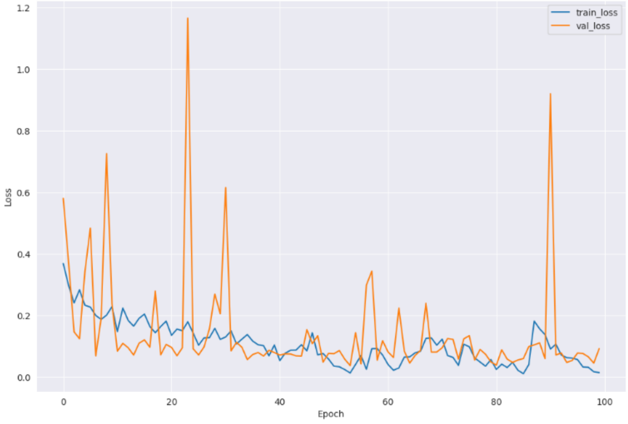

Fig. 6. Training loss in and validation loss fine-tuning in two classes normal and scoliosis of our model.

Fig. 7 indicates the confusion matrix of two-class (i.e., scoliosis and normal spine) in 700 pictures.

C. Scenario 2: The Results of Classifying X-Ray Images Into Two Classes: Spondylolisthesis and Normal Spine

Table III indicates the highest result of EfficientNetB3 in transfer learning (i.e., 100%) and other models also achieved a high result (i.e., > 95%). Moreover, Table IV shows a reduction in the results of EfficientNetB3, VGG19, and ResNet101 but our model has signification growth (i.e., 99.43%).

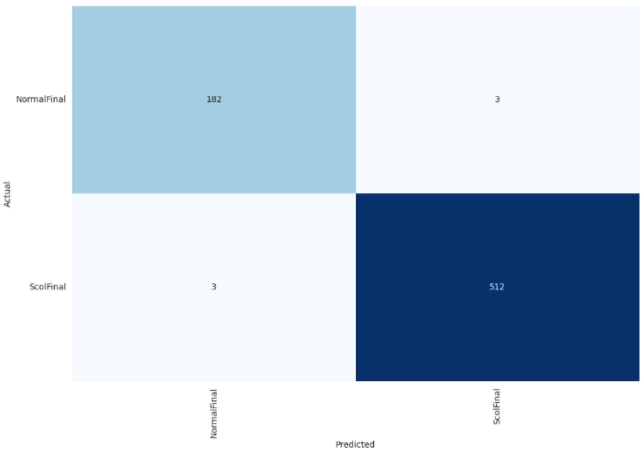

Fig. 7. Confusion matrix in fine-tuning in two classes normal and scoliosis of our model.

TABLE III. THE ACCURACY OF CLASSIFYING X-RAY IMAGES INTO TWO CLASSES: NORMAL SPINE AND SPONDYLOLISTHESIS IN TRANSFER LEARNING, FOR EACH DEEP LEARNING MODEL

Model	Transfer learning				
	Val acc	Test acc	Precision	Recall	F1
EfficientNetB3	99.86%	100.00%	100.00%	100.00%	100.00%
DenseNet169	97.57%	97.71%	97.72%	97.71%	97.72%
VGG19	99.71%	99.57%	99.57%	99.57%	99.57%
ResNet101	99.86%	99.86%	99.86%	99.86%	99.86%
Our Model	**96.43%**	**95.57%**	**95.59%**	**95.57%**	**95.57%**

TABLE IV. THE ACCURACY OF CLASSIFYING X-RAY IMAGES INTO TWO CLASSES: NORMAL SPINE AND SPONDYLOLISTHESIS IN FINE TUNING, FOR EACH DEEP LEARNING MODEL

Model	Fine tuning				
	Val acc	Test acc	Precision	Recall	F1
EfficientNetB3	99.86%	99.14%	99.14%	99.14%	99.14%
DenseNet169	99.14%	98.86%	98.87%	98.86%	98.86%
VGG19	93.29%	91.43%	91.50%	91.43%	91.44%
ResNet101	97.14%	97.00%	97.03%	97.00%	97.00%
Our Model	**99.57%**	**99.43%**	**99.43%**	**99.43%**	**99.43%**

Fig. 8 and Fig. 9 in this experiment explain training accuracy and training loss in our model for two classes of normal and spondylolisthesis which low test loss (i.e., ~0%).

The outcome confusion matrix is finally displayed in Fig. 10, demonstrating the excellent performance of our model.

D. *Scenario 3: The Results of Classifying X-Ray Images into Three Classes: Spondylolisthesis, Scoliosis, and Normal Spine*

Table V and Table VI illustrate in transfer learning the ResNet101 reaches the highest accuracy value over the three statistical measures with a validation accuracy of 99.00%, test accuracy of 97.71%, and F1 score of 97.72%. However, our model performed achieved the lowest rank in transfer learning with a validation accuracy of 82.00%, test accuracy of 80.71%, and F1 score of 79.97%. The final result is only improved in fine-tuning after our research added more layers and that proves our achievements exactly when our model gets a validation accuracy of 99.00%, test accuracy of 97.86%, and F1 score of 97.86%.

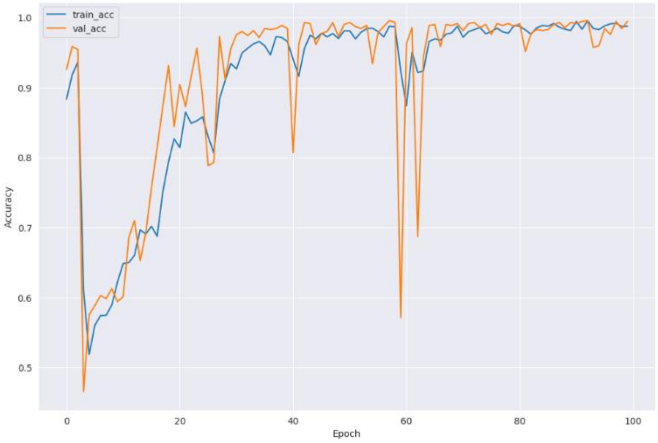

Fig. 8. Training accuracy and validation accuracy in fine-tuning in two classes normal and spondylolisthesis of our model.

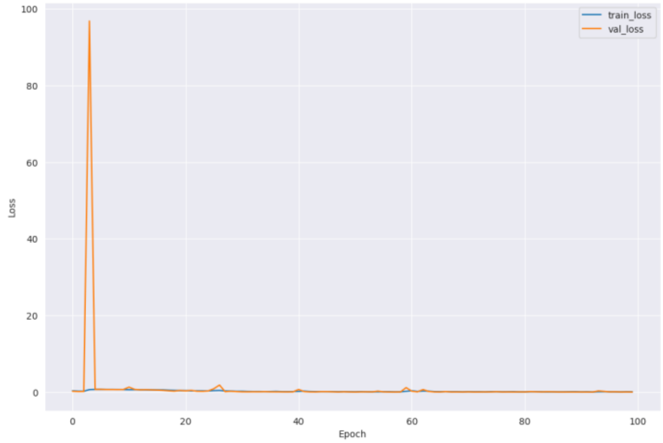

Fig. 9. Training loss in and validation loss fine-tuning in two classes normal and spondylolisthesis of our model.

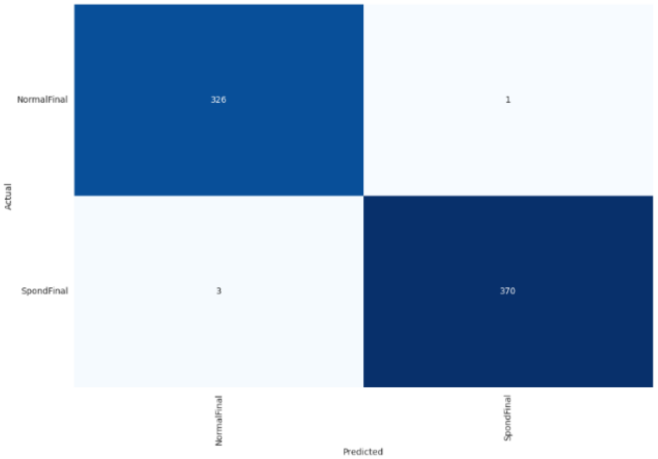

Fig. 10. Confusion matrix in fine-tuning in two classes normal and spondylolisthesis of our model.

TABLE V. THE ACCURACY OF CLASSIFYING X-RAY IMAGES INTO THREE CLASSES: NORMAL SPINE, SCOLIOSIS, AND SPONDYLOLISTHESIS IN TRANSFER LEARNING, FOR EACH DEEP LEARNING MODEL

Model	Transfer learning				
	Val acc	Test acc	Precision	Recall	F1
EfficientNetB3	98.86%	97.71%	97.77%	97.71%	97.73%
DenseNet169	88.43%	86.43%	87.27%	86.43%	86.67%
VGG19	91.86%	64.43%	89.40%	89.00%	89.03%
ResNet101	99.00%	97.71%	97.74%	97.71%	97.72%
Our Model	**82.00%**	**80.71%**	**80.45%**	**80.71%**	**79.97%**

TABLE VI. THE ACCURACY OF CLASSIFYING X-RAY IMAGES INTO THREE CLASSES: NORMAL SPINE, SCOLIOSIS, AND SPONDYLOLISTHESIS IN FINE TUNING, FOR EACH DEEP LEARNING MODEL

Model	Fine tuning				
	Val acc	Test acc	Precision	Recall	F1
EfficientNetB3	96.86%	96.71%	96.75%	96.71%	96.72%
DenseNet169	95.71%	93.57%	93.65%	93.57%	93.60%
VGG19	69.57%	26.00%	53.17%	67.00%	59.10%
ResNet101	84.29%	82.57%	82.74%	82.57%	82.14%
Our Model	**99.00%**	**97.86%**	**97.88%**	**97.86%**	**97.86%**

The training and validation progress curves for a scenario run of the best-performing model are displayed in Fig. 11 and Fig. 12. A model's performance on the training data is measured by training accuracy, which indicates how well the model can learn from the given instances.

The model is guided to reduce mistakes during training by measuring the difference between anticipated and actual values in the training set, which is known as training loss. Validation loss is a crucial metric for assessing the generalization performance of the model, replicating this procedure on an independent dataset.

Fig. 12 shows the sample confusion matrix for three classes of classification. This important step makes it possible for us to see a more intuitive comparison of the results achieved. Fig. 13 illustrates the final result displayed in the SHAP value of Partition Explainer in Fig. 14 which is an excellent way to present visually and provides an overall view for experts and medical teams.

E. Comparison with others State-of-the-art Methods

To examine the accuracy of the proposed model that our article has just given out in the previous section, we compare the accuracy score of the proposed model with other CNN architectures in Table VII, which are EfficientNetB3, DenseNet169, VGG19, and ResNet101.

Our comparison serves as a standardized benchmark, allowing researchers to evaluate the performance of new approaches, identify strengths and weaknesses, and push the boundaries of what is achievable. This process fosters healthy competition, driving innovation and motivating the community to build upon successful methodologies. Assessing generalization across diverse datasets, understanding resource utilization, and uncovering limitations are key outcomes of such comparisons. Moreover, it ensures reproducibility, aligns research with community standards and guides future endeavors toward addressing challenges and improving the overall state of the art in deep learning.

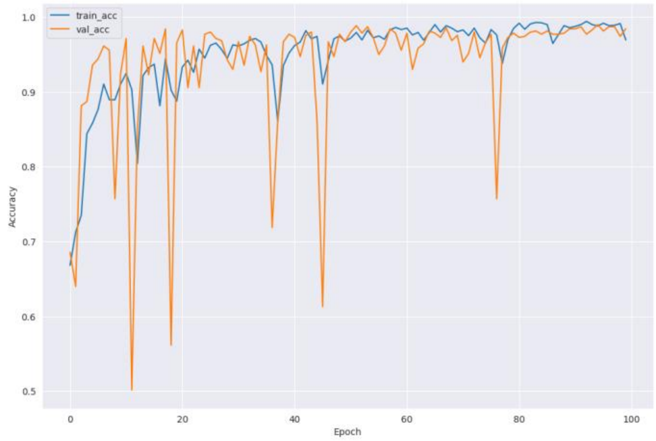

Fig. 11. Training accuracy and validation accuracy in fine-tuning in three classes of our model.

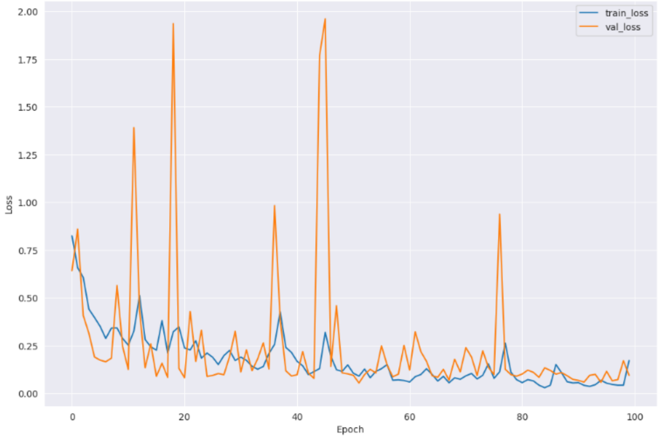

Fig. 12. Training loss in and validation loss fine-tuning in three classes of our model.

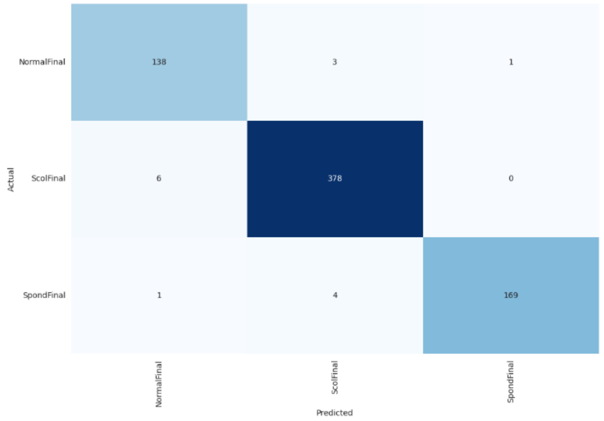

Fig. 13. Confusion matrix in fine-tuning in three classes of our model.

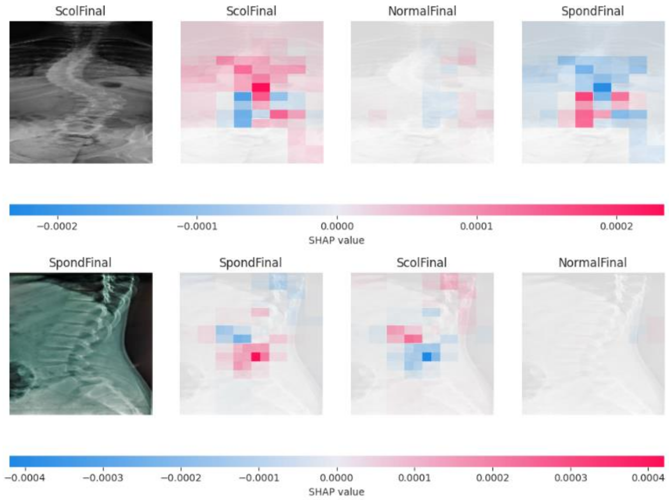

Fig. 14. The final result with Partition Explainer.

TABLE VII. COMPARISON WITH OTHERS STATE-OF-THE-ART METHODS

Ref.	***Proposed***	***Accuracy***
Peiji Chen et al.	ResNet and Faster R-CNN	90.87%
Joddat Fatima et al.	Mask RCNN and YOLOv5	94.69%
Shuman Han et al.	ROC and Cobb	77.9% ~ 93.6%
Wahyu Caesarendra et al.	AutoSpine-Net	90.00%
Fatih Varçın et al.	MobileNet	99.99%
Deepika Saravagi et al.	InceptionV3 and VGG16	96.00% ~ 98.00%
Fatih Varçın et al.	AlexNet and GoogleLeNet	91.67%
Mohammad Fraiwan et al.	DensNet-201	96.73% ~ 98.02%
Deepika Saravagi et al.	VGG16	98.00%
Arslan Amin et al.	EfficientNet	86.00%
Ariana Alejandra Andrews Interiano et al.	InceptionResNet, MobileNet, and EfficientNet	98.01%
Dalwinder Singh et al.	SMO	96.00%
Proposed model		**97.86%**

V. CONCLUSION

Our newly developed model showcases commendable performance in classifying vertebrae X-ray images, specifically distinguishing between normal spines, scoliosis, and spondylolisthesis for critical medical applications. The model exhibits a remarkable validation accuracy of 99.00%, a robust test accuracy of 97.86%, and an F1 score of 97.86%, underscoring its efficacy in accurately identifying and categorizing spinal conditions. The success of our model can be attributed to strategic modifications, including the incorporation of dense and dropout layers into the Xception model, coupled with fine-tuning various settings, resulting in a substantial improvement in overall accuracy.

Transfer learning played a pivotal role in our approach, leveraging the pre-trained Xception model as a foundation. This technique involves utilizing knowledge gained from a task-specific source domain, in this case, the general image recognition capabilities of the Xception model, and applying it to our specific task of vertebrae classification. Fine-tuning further refined the model's performance by adjusting its parameters to align with the intricacies of our dataset. This process enhances the model's ability to discern subtle features in X-ray images, enabling more accurate and reliable classification.

While our current model exhibits exceptional results, there are inherent limitations. As with any machine learning model, it is crucial to recognize the boundaries of its capabilities. The accuracy achieved is not absolute, and there may be instances where misclassifications occur. Understanding these limitations is paramount for responsible deployment in medical contexts.

Looking forward, our focus revolves around continuous improvement. By incorporating a wider variety of X-ray images, we aim to ensure the model's adaptability to diverse patient demographics and anatomical variations, thereby fortifying its utility in clinical settings. The incorporation of interpretability tools such as Partition Explainer and SHAP values enhances the model's transparency, providing insights into decision-making processes.

In conclusion, our pursuit is anchored in advancing the classification of vertebrae X-ray images, contributing significantly to the medical field's diagnostic capabilities. As we navigate future developments, we remain dedicated to the responsible and progressive evolution of our model for the betterment of patient care and medical decision-making.

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Toward Enhanced Customer Transaction Insights: An Apriori Algorithm-based Analysis of Sales Patterns at University Industrial Corporation

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***Abstract*—The University Industrial Corporation (CIU) at the National University of Jaen offers a range of consumable products, encompassing nectar, water, coffee, chocolate, and chocoteja. However, its sales transactions function without a systematic analysis. To address this, the study gathered and analyzed sales data from March to November 2023, aiming to identify and delineate associations among frequently co-purchased products, revealing underlying interdependencies and associations. Employing text mining methodologies, this study preprocessed and analyzed 1542 sales records using the Apriori algorithm, culminating in the extraction of 17 association rules. Among these rules, three standout associations were uncovered: the purchase of chocolate, chocoteja and water suggests a purchase of nectar; chocolate, nectar and water acquisitions correlate with chocoteja purchases; lastly chocolate and nectar purchases are associated with chocoteja acquisitions. These findings provide insights to augment potential production adjustments within the CIU, enabling the leveraging of established associations to boost sales and revenue. Moreover, the identified rules serve as a cornerstone for decision-makers, actionable guidance for stakeholders, enabling the identification of co-purchased products, fostering informed production planning, fine-tuning marketing strategies for customer relationship management (CRM), and enhancing CIU's market competitiveness and profitability.**

Keywords*—*Apriori algorithm; association rules; Customer Relationship Management (CRM); decision making; text mining

I. Introduction

Recent advancements in information technologies have propelled transformative opportunities in several public and private institutions, streamlining services and operational efficiencies for the populations. Consequently, this technological progression has empowered companies to acquire, store, analyze, and interpret vast volumes of data, marking a pivotal shift in the significance of dataset. Thus, the consequential impacts transcend the technological domain, influencing the restructuring of business strategies and marketing activities [1].

Simultaneously, the widespread accessibility of the Internet and the burgeoning domain of e-commerce have accumulated extensive repositories of customer transactional data within websites. Employing sophisticated data mining techniques has enabled the aggregation and analysis of these massive datasets within complex web structures [2], [3]. This revolutionizing data mining movement has significantly shaped the information landscape and society, facilitating the process of transforming large amounts of data into valuable insights and knowledge [4]. The fundamental objective of data mining remains centered on the discovery of high-frequency sets, fostering the extraction of implicit associations, subsequently aiding in informed decision-making. As observed in [5], there exists an intriguing correlation between seemingly unrelated products, such as diapers and beer, co-placement of which resulted in a mutual sales upsurge.

Moreover, text mining, a subset of data mining, involves the transformation of unstructured and semi-structured textual data from vast databases into digital formats for information extraction. Its functional applications span a wide range, including semantic text mining, word feature mining, association rule mining, text clustering analysis, and trend prediction [6].

On the other hand, data mining association algorithms serve as indispensable tools, widely embraced by major tech companies such as Amazon, Google, Netflix, Facebook, and Twitter. These algorithms effectively uncover intricate interrelations among variables within extensive datasets. By extracting interesting correlations, frequencies, and patterns from association rules [7], proving instrumental in predicting relevant elements in subsequent analysis [8].

The array of association rule algorithms spans the Apriori algorithm, Frequent Pattern (FP)-Tree, Equivalence Class Clustering, bottom-up Lattice Traversal (ECLAT) algorithm, and the gray association method. Notably, the Apriori algorithm developed by Agrawal and Srikant [9], stand as the classical paradigm for mining frequent itemset in the domain of association rules analysis [10]. This algorithm operates on a bottom-up search methodology, progressively assembling generated itemset to ensure the identification of frequent item subsets.

The University Industrial Corporation (CIU), an integral component of the Production Center of Goods and Services at the National University of Jaen (UNJ), plays a pivotal role in advancing academic, research, and production endeavors in alignment with the institution's overarching goals. As a part of its unwavering commitment to foster scientific inquiry, promote the UNJ brand, and deliver competitive, high-quality products, the CIU takes the lead in exploring new market opportunities and devising scalable, replicable business strategies.

This study endeavors to perform a comprehensive analysis of product purchases by employing association rules. To accomplish this objective, the research leveraged the renowned Apriori algorithm, which adeptly identifies frequent items within transactional databases. The research dataset, spanning sales from March to November 2023, meticulously focuses on key products offered by the CIU, including chocolate, chocoteja, water, nectar, and coffee.

The organization of this paper is as follows: Section I gives a brief background on data mining. Section II, presents the related research, highlighting key advancements and gaps in the field. Section III outlines the rigorous methodology employed in this study. The core findings, accompanied by in-depth analysis and contextual discussions are conducting in Section IV, and Section V draws the meaningful conclusions, and outlines avenues for future research.

II. State of the Art

The implementation of association rules through the Apriori algorithm has been used in different aspects of knowledge, showcasing its versatility and applicability in diverse fields such as marketing, health sciences, computer science, transportation, education, labor, and mining. In marketing, its utility extended to the dissection of purchase transaction-based product promotions [8], recommending e-commerce links [2], and characterizing e-customer behavior to discern purchase patterns among two customer groups [3]. Noteworthy studies have included analysis of purchased products [11], examination of consumer purchasing patterns [12], encompassing market basket analysis [13], and online shopping through RFMDR model [14]. Furthermore, it found practical application in minimum spanning tree-based shopping [15], and Internet marketing strategies in the cosmetics sales in Taiwan [16].

In the realm of health sciences, association rules' usage facilitated the sifting of potential analgesics from a pool of 311 cases treated with compounded drug prescriptions, extracting data on clinical symptoms and types of Chinese herbs [17]. Notably, it facilitated the development of an automatic diagnostic system for breast cancer detection [18], and the identification of distinguishing factors between dementia patients, and caregivers linked to long-term care services [19]. Furthermore, it revealed a set of frequent items aiding in fetal anomaly detection [20], and uncovered the primary combination of Chinese herbs for Alzheimer's disease treatment within acupuncture practices [21]. Research efforts extended into investigating acupuncture point combinations for the treatment of hemiparesis [22], exploring protein-gene interactions from omics data [23], and identifying links between Polycystic Ovary Syndrome (PCOS), and hormonal imbalances utilizing the DEODORANT model [24]. Associations between attributes characterizing the perfusion patterns in normal subjects illuminated the diagnosis of Alzheimer’s disease [25], unraveling pathogenesis linked to thyroid disease [26], analysis of comorbidity in residents afflicted by chronic diseases [27], and classification of anxiety in palliative patients [28]. Moreover, it delineated specific correlations between individuals with dementia and caregivers based on various dementia subtypes [29].

In the Information Technology (IT) context, a methodological approach has been proposed to advance requirements engineering within the enterprise software domain [30]. Also, significant contributions include outlier cleaning in network measurement data [31], processing voluminous datasets through membrane computing models [32], and developing mobile e-commerce recommender systems for online shopping [33]. Additionally, notable efforts have been directed towards bolstering the security of global cyberspace [34] and enhancing the water wave optimization algorithm [35].

In the transportation sector, specific methodologies have been tailored to scrutinize and process data derived from Iranian railroad accidents [36], and identifying risk factors associated with freight truck accidents [37]. Educational research has surfaced various funding initiatives. Among these are studies analyzing user behavior when requesting texts from the library loans [38], uncovering natural products and anti-migraine nutraceuticals from extensive classical medical literature collections [39], and rule extraction from the scoring records of 2002 computer science students at the Mongolian University of Science and Technology [40].

Within the domain of employment, through investigations were conducted to explore the correlations between employment status, and the employability indicators of maritime graduates [41]. Another study proposed a customer potential value matrix, designed to segment applicants based on their potential value and willingness to engage in purchases, thereby enhancing the scope of customer segmentation strategies [42]. Lastly, in the mining sector, an investigation scrutinized the link between structural deformation and gold mineralization, offering valuable insights into the intricate relationship [43].

This study is based on the pressing need to integrate innovative and technological approaches in the business environment. By using Apriori algorithms and association rules in CIU-Jaen, the complexity of large volumes of data is explored, revealing latent patterns and underlying relationships, that generate opportunities for improvement and facilitating agile decision-making. The exhaustive analysis of the association rules allows deepening the knowledge of the operational dynamics and the behavior of the customers, unveiling behavioral patterns and preferences, facilitating the design of solid strategies to boost growth and ensure sustainable development. The adoption of technological tools and data-based strategies within the business field is a key step to stimulate and promote innovation and adaptability in a competitive and ever-evolving environment.

III. Methodology

The research consists of four crucial steps and is visually represented in Fig. 1:

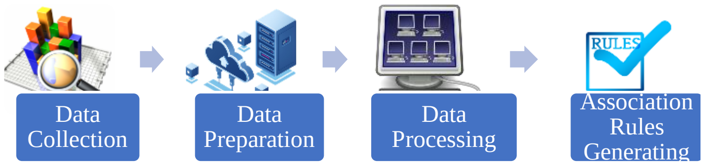
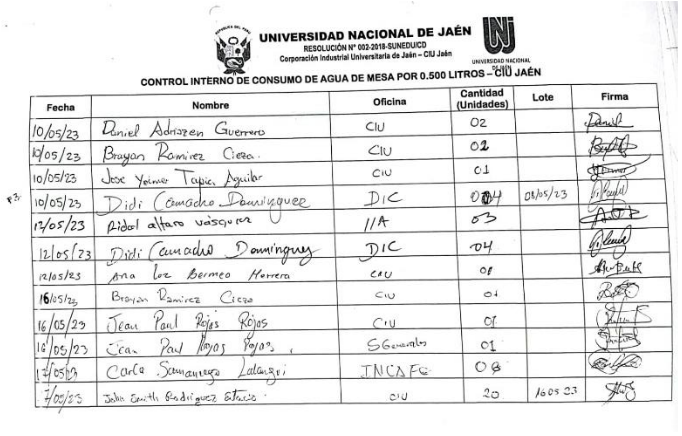


Fig. 1. Apriori algorithm schema.

A. Data Collection

The dataset was meticulously procured a comprehensive dataset from the sales register maintained by the University Industrial Corporation. The corporation employs a manual record-keeping register paper, which includes detailed information about products, such as chocolate, chocoteja, coffee, nectar, and water. The data collection efforts spanned form March to November 2023 as shows in Fig. 2.



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CONTROL INTERNO DE CONSUMO DE AGUA DE MESA POR 0.500 LITROS – CIU JAÉN

Fecha	Nombre	Oficina	Cantidad (Unidades)	Lote	Firma
10/05/23	Daniel Adriazen Guerrero	CIU	02		Daniel
10/05/23	Brayan Ramirez Cieza.	CIU	02		
10/05/23	Jose Yeimer Tapia Aguilar	CIU	01		
10/05/23	Didi Camacho Dominguez	DIC	04	08/05/23	
12/05/23	Fidel alfaro vásquez	IIA	03		
12/05/23	Didi Camacho Dominguez	DIC	04		
12/05/23	Ana Luz Bermeo Herrera	CIU	01		
16/05/23	Brayan Ramirez Cieza	CIU	01		
16/05/23	Jean Paul Rojas Rojas	CIU	01		
16/05/23	Jean Paul Rojas Rojas ,	SGenerales	01		
17/05/23	Carla Samaniego Lalangui	INCAFE	08		
17/05/23	John Smith Rodriguez Estacio .	CIU	20	16 05 23	

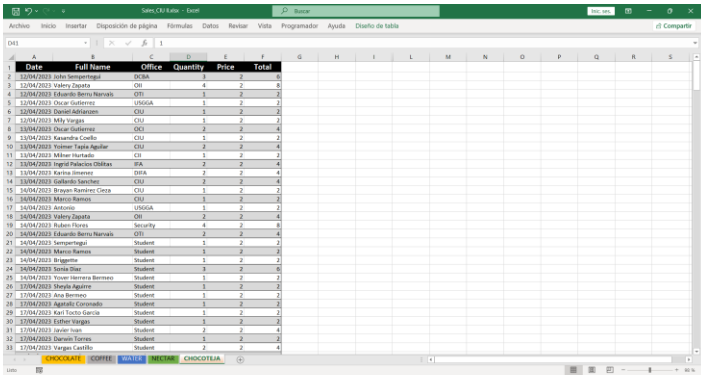
Fig. 2. CIU-Jaen data collection.

B. Data Preparation

The acquired data was diligently organized within an Excel worksheet (.xlsx), delineating key attributes such as date, client details, product names, work office, quantity and pricing fields, which is depicted in Fig. 3. Subsequently, a structured flat file (.csv) was generated, employing comma-separated values for seamless data manipulation.

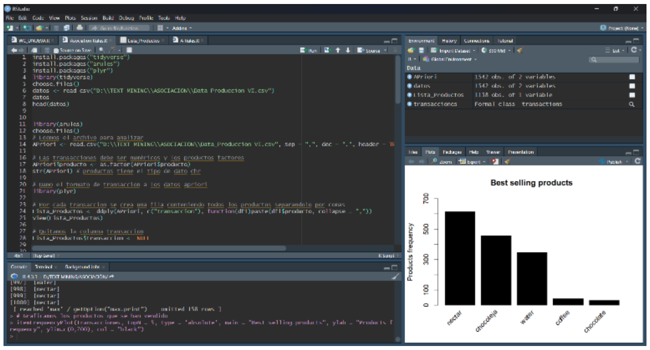
C. Data Processing

Leveraging the powerful capabilities of the R software ecosystem. Specifically, we harnessed the tidyverse, arules, plyr, and arulesviz libraries to transform raw data into meaningful insights, as shown in Fig. 4. The focus of the study was on extracting association rules, a critical step in uncovering hidden patterns and relationships within the dataset. To enhance interpretability, the visualization of the extracted rules was using the arulesviz library. The graphical representations employed three distinct layouts: Fruchterman-Reingold, Kamada-Kawai, and Reingold-Tilford graphs. These layouts elegantly depicted the interconnected nodes corresponding to products like chocolate, chocoteja, nectar, water, and coffee. Arrows extending from antecedent to consequent nodes illustrated the direction of association, emphasizing the sequential relationships. The size of circles positioned at the nexus of these arrows conveyed support values, reflecting the frequency of occurrence for each rule. Additionally, coloration was strategically applied to denote the associated lift values.



	A	B	C	D	E	F
1	Date	Full Name	Office	Quantity	Price	Total
2	12/04/2023	John Sempertegui	DCBA	3	2	6
3	12/04/2023	Valery Zapata	OII	4	2	8
4	12/04/2023	Eduardo Berru Narvais	OTI	1	2	2
5	12/04/2023	Oscar Gutierrez	USGGA	1	2	2
6	12/04/2023	Daniel Adrianzen	CIU	1	2	2
7	12/04/2023	Mily Vargas	CIU	1	2	2
8	13/04/2023	Oscar Gutierrez	OCI	2	2	4
9	13/04/2023	Kasandra Coello	CIU	1	2	2
10	13/04/2023	Yoimer Tapia Aguilar	CIU	2	2	4
11	13/04/2023	Milner Hurtado	CII	1	2	2
12	13/04/2023	Ingrid Palacios Oblitas	IFA	2	2	4
13	13/04/2023	Karina Jimenez	DIFA	2	2	4
14	13/04/2023	Gallardo Sanchez	CIU	2	2	4
15	14/04/2023	Brayan Ramirez Cieza	CIU	1	2	2
16	14/04/2023	Marco Ramos	CIU	1	2	2
17	14/04/2023	Antonio	USGGA	1	2	2
18	14/04/2023	Valery Zapata	OII	2	2	4
19	14/04/2023	Ruben Flores	Security	4	2	8
20	14/04/2023	Eduardo Berru Narvais	OTI	2	2	4
21	14/04/2023	Sempertegui	Student	1	2	2
22	14/04/2023	Marco Ramos	Student	1	2	2
23	14/04/2023	Briggette	Student	1	2	2
24	14/04/2023	Sonia Diaz	Student	3	2	6
25	14/04/2023	Yover Herrera Bermeo	Student	1	2	2
26	17/04/2023	Sheyla Aguirre	Student	1	2	2
27	17/04/2023	Ana Bermeo	Student	1	2	2
28	17/04/2023	Agataliz Coronado	Student	1	2	2
29	17/04/2023	Kari Tocto Garcia	Student	1	2	2
30	17/04/2023	Esther Vargas	Student	1	2	2
31	17/04/2023	Javier Ivan	Student	2	2	4
32	17/04/2023	Darwin Torres	Student	1	2	2
33	17/04/2023	Vargas Castillo	Student	2	2	4

Fig. 3. Data stored in excel.



```
install.packages("tidyverse")
install.packages("arules")
install.packages("plyr")
library(tidyverse)
choose.files()
datos <- read.csv("D:\\TEXT MINING\\ASOCIACION\\Data Produccion VI.csv")
datos
head(datos)


library(arules)
choose.files()
# Leemos el archivo para analizar
APriori <- read.csv("D:\\TEXT MINING\\ASOCIACION\\Data_Produccion VI.csv", sep = ",", dec = ".", header = TR

# Las transacciones debe ser numéricos y los productos factores
APriori$producto <- as.factor(APriori$producto)
str(APriori) # productos tiene el tipo de dato chr

# Damo el formato de transaccion a los datos apriori
library(plyr)

# Por cada transaccion se crea una fila conteniendo todos los productos separandolo por comas
Lista_Productos <- ddply(APriori, c("Transaccion"), function(df1)paste(df1$producto, collapse = ","))
View(Lista_Productos)

# Quitamos la columna transaccion
Lista_Productos$Transaccion <- NULL
```

```
R 4.3.1 · D:/TEXT MINING/ASOCIACIÓN/
[997]  [water]
[998]  [nectar]
[999]  [nectar]
[1000] [nectar]
 [ reached 'max' / getOption("max.print") -- omitted 158 rows ]
> # Graficamos los productos que se han vendido
> itemFrequencyPlot(transacciones, topN = 5, type = 'absolute', main = "Best selling products", ylab = "Products f
requency", ylim = c(0,700), col = "black")
>
```

```
Data
APriori          1542 obs. of 2 variables
datos            1542 obs. of 2 variables
Lista_Productos  1158 obs. of 1 variable
transacciones    Formal class  transactions
```

Fig. 4. Use R software for data processing.

D. Association Rules Generating

Three criteria were used to identify the relationship: support confidence, and lift.

- Support: It is the percentage of transactions in the database that contain both itemset A and B. The degree of support A ⟹ B in the rule A ⟹ B, is the probability that a given set of itemset contain A and B, which is expressed by the value of probability P(AUB) [44]. A high degree of support indicates that the mining results are consistent and that the provided rules are effective association rules. On the other side, a low degree of support indicates that the data mining results appear only occasionally and the provided rules have little value for the research. Eq. (1) represents the definition of support of the association rule between A and B [45].

$$\text{Support } A \Longrightarrow B = P\,(A \cap B) = \frac{|A \cup B|}{|D|} \qquad (1)$$

- Confidence: It is the percentage of transactions in database D with item set A that also contain item set B [5]. Confidence is calculated using the conditional probability and is expressed relative to the item set support [46] and is represented by Eq. (2):

$$\text{Confidence A} \Longrightarrow \text{B} = \frac{support\ (A \Rightarrow B)}{support\ (A)} = \frac{P(\text{A} \cap \text{B})}{\text{P(A)}} \qquad (2)$$

In Eq. (2), support $(A \Longrightarrow B)$ is the number of transactions containing the itemset A and B, support (A) is the number of transactions containing the itemset A [44].

- Lift: Used to measure the frequency of A and B together, if both sets of items are statistically independent of each other [47]. The calculation is as shown in Eq. (3):

$$\text{Lift A} \Longrightarrow \text{B} = \frac{confidence\ (A \Rightarrow B)}{support\ (A)} = \frac{P(\text{A} \cap \text{B})}{\text{P(A)P(B)}} \qquad (3)$$

The lift of the rule A ⟹ B shows how much the probability of B will increase, if A occurs [48]. There are three cases:

- When lift $(A \Longrightarrow B) > 1$, then there is a positive interdependence between the antecedent and consequent; so, the rule is considered valuable.
- When lift $(A \Longrightarrow B) < 1$, then there is a negative interdependence between the antecedent and consequent.
- When $(A \Longrightarrow B) = 1$, then A and B are independent and there is no correlation between them.

Therefore, the higher the measure of lift, the higher the interest of the generated rules will be. So, with the help of this measure, it will classify the rules that meet the minimum thresholds of support and confidence.

IV. Result Analysis and Discussions

The extracted association rules, meticulously presented in Table I, offer profound insights into the intricate relationships and patterns inherent in the consumer transactions within the dataset. Simultaneously, the graphical representation in Fig. 5, vividly illustrates the frequency distribution of the sold products. Upon discerning the bar chart, a discernible hierarchy in product popularity emerges. Foremost among the products is nectar, indisputably leading in sales volume. Subsequently, chocoteja claims the second position, closely followed by water in third. However, it is imperative to note that, coffee and chocolate, manifest a comparatively lower acceptance rate among consumers.

This analysis not only informs products positioning within the market, but also lays the foundation for strategic decision-making, offering a profound understanding of consumer preferences and market dynamics. The identification of less favored products underscores potential areas for marketing enhancement, contributing to an informed approach for maximizing sales and overall business efficacy.

The outcomes showed in Table I illustrated 17 association rules, each distinguished by a pivotal support attribute, signifying the frequency of rule occurrence within the dataset. It's important to state that, a higher threshold correlates with an augmented frequency of rule manifestation. For instance, the acquisition of chocoteja and nectar frequently coincides with chocoteja, and vice versa.

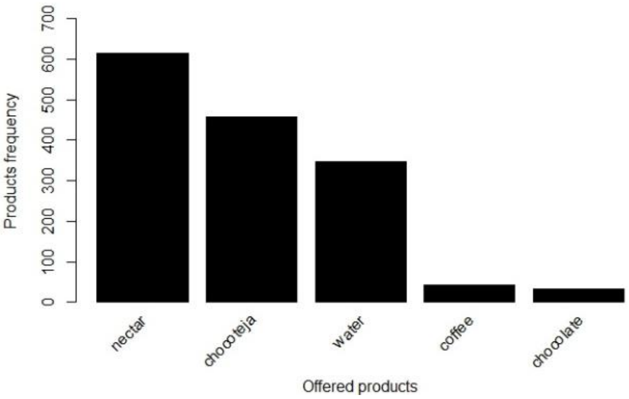


Fig. 5. Bar chart of best-selling products.

TABLE. I ASSOCIATION RULES OBTAINED

Nº	Association rules	Support	Confidence	Lift	Leverage
1	{chocolate} => {chocoteja}	0.0181	0.6563	1.6593	0.0072
2	{chocolate} => {nectar}	0.0173	0.6250	1.1787	0.0026
3	{coffee} => {chocoteja}	0.0225	0.6190	1.5652	0.0081
4	{coffee} => {nectar}	0.0268	0.7381	1.3920	0.0075
5	{chocolate, water} => {chocoteja}	0.0121	0.8235	2.0822	0.0063
6	{chocolate, chocoteja} => {water}	0.0121	0.6667	2.2184	0.0066
7	{chocolate, water} => {nectar}	0.0130	0.8824	1.6641	0.0052
8	{chocolate, nectar} => {water}	0.0130	0.7500	2.4957	0.0078
9	{chocolate, chocoteja} => {nectar}	0.0155	0.8571	1.6166	0.0059
10	{chocolate, nectar} => {chocoteja}	0.0155	0.9000	2.2755	0.0087
11	{coffee, water} => {nectar}	0.0199	0.9200	1.7351	0.0084
12	{coffee, nectar} => {water}	0.0199	0.7419	2.4689	0.0118
13	{chocoteja, water} => {nectar}	0.0484	0.6154	1.1606	0.0067
14	{chocolate, chocoteja, water} => {nectar}	0.0121	1.0000	1.8860	0.0057
15	{chocolate, nectar, water} => {chocoteja}	0.0121	0.9333	2.3598	0.0070
16	{chocolate, chocoteja, nectar} => {water}	0.0121	0.7778	2.5881	0.0074
17	{chocoteja, coffee, water} => {nectar}	0.0121	0.9333	1.7603	0.0052

Table I comprehensively details 17 rules scrutinized with 1542 purchase records involving five different products. Each entry includes a robust rule alongside its corresponding metrics, including support, confidence, lift and leverage. Although the vast dataset and modest support might diminish the impact on confidence verification, three strong rules, considering the aforementioned parameters, warrant attention:

- Rule 14: {chocolate, chocoteja, water} ⇒{nectar}
- Rule 15: {chocolate, nectar, water} ⇒{chocoteja}
- Rule 10: {chocolate, nectar} ⇒{chocoteja}

Examining rule 14, the support stands at 1.21%, confidence at 100%, lift at 1.886, and leverage at 0.00557. These results have a perfect confidence, indicating that whenever chocolate, chocoteja, and water are present, nectar is also present. The high lift value; suggest a strong association between the items, making it a significant rule.

It is the percentage of transactions in the database that contain both itemset A and B. The degree Rule 15, with a support of 1.21%, confidence of 93.33%, lift of 2.3598, and leverage of 0.007, indicating that when chocolate, nectar, and water are present, there is a strong likelihood of chocoteja being present. The lift of 2.3598 suggests a significant association.

Lastly, rule 10 boasting 1.55% support, 90% confidence, 0.0087 leverage, and 2.2755 lift. The high confidence and lift make this rule significant. It indicates a strong association between chocolate and nectar leading to the presence of chocoteja. These selected rules are not only supported by high confidence but also exhibit substantial lift, indicating that the items involved are more likely to be purchased together than if they were chosen randomly. Leverage provides additional insights into the strength of the association, and in these cases, it complements the high confidence and lift values.

The Fig. 6 displays a grouped matrix for 17 rules, where rows represent the RHS (Right Hand Side), columns represent the LHS (Left Hand Side) items, and cells convey information about the strength of association between these elements. Colors denote the lift of products, while size represents the support between them. This graphical representation enhances the comprehension of association relationships between LHS and RHS elements based on metrics such as support and lift. Such a visual approach aids in identifying patterns and interpreting association rules within the context of CIU product purchases.

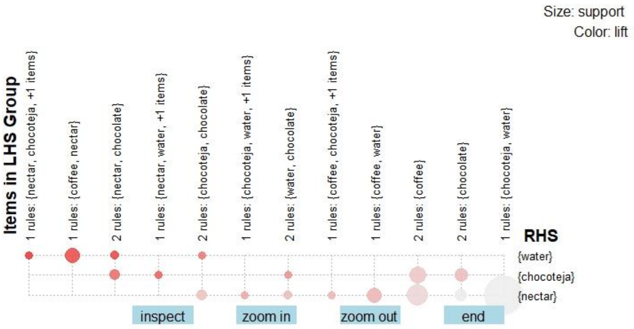


Fig. 6. Grouped matrix for 17 rules.

In the Fig. 7 shown below, there is a visual representation of the association rules extracted through the Apriori algorithm. Specifically, the use of the “htmlwidget” engine enables an interactive experience, allowing users to dynamically explore and analyze the generated rules. For instance, by clicking on a node or edge, users can access detailed information about the rule, including metrics such as support, confidence, and lift. This visualization proves valuable in comprehending purchase patterns and relationships among products, leading to meaningful applications in marketing strategies and business decision-making.

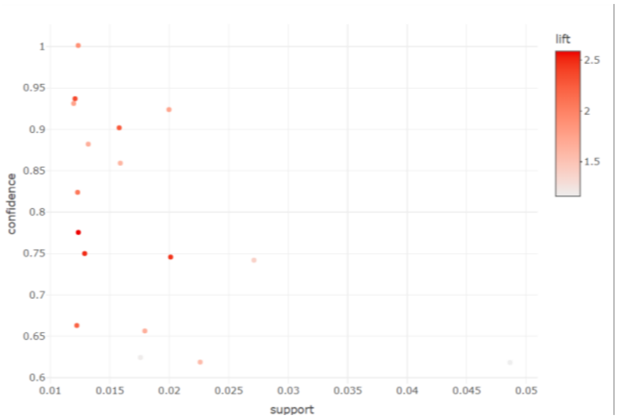


Fig. 7. Scatter plot for 17 association rules.

Analysis of Association Rules

Fig. 8, 9 and 10 depict the association rules, particularly highlighting the rule "chocolate, chocoteja, water ⟹ nectar”, showcasing a modest support but a notably high confidence value. Similar observations are made for the rules "chocolate, nectar, water ⟹ chocoteja” and "chocolate, nectar ⟹ chocoteja”. The graphical and Table II representations affirm the consistency and interrelations of these rules, with variations attributed to the arrangement elements.

The application of the Fruchterman-Reingold (FR) algorithm, grounded in particle physics principles, is evident in Fig 8. Guided by the notions that connected nodes should be proximate, and others should be proximate, and others should maintain a suitable distance [49]. The FR method considers a graph as a collection of vertices connected by edges with two types of forces acting on the vertices. The graph is generated with 500 iterations and an initial temperature parameter of 4.69.

For the creation of two-dimensional graphs, the Kamada-Kawai (KK) method that conceptualizes a graph as a system of spring, was employed [50]. Fig. 9 illustrates the KK algorithm with 1100 iterations and a constant vertex attraction parameter set to 22. In the KK algorithm, the placement of nodes ensures that their visual distance corresponds proportionally to their plotted distance.

TABLE. II STRONG ASSOCIATION RULES OBTAINED

Nº	Association rules	Support	Confidence	Lift	Leverage
1	{chocolate, chocoteja, water} => {nectar}	0.0121	1.0000	1.8860	0.0057
2	{chocolate, nectar, water} => {chocoteja}	0.0121	0.9333	2.3598	0.0070
3	{chocolate, nectar} => {chocoteja}	0.0155	0.9000	2.2755	0.0087

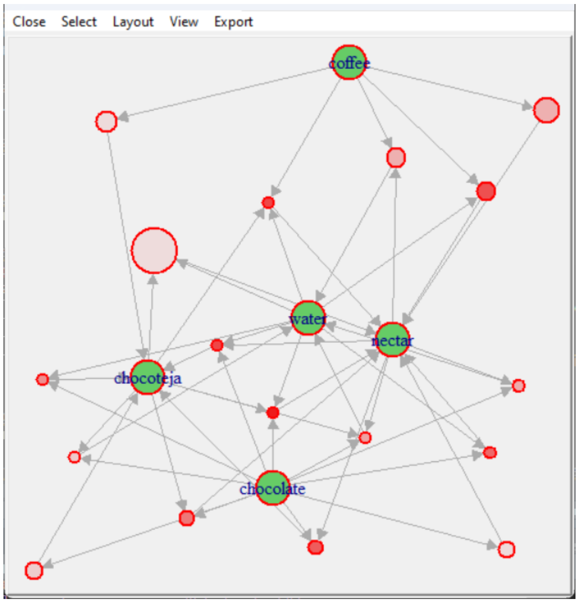


Fig. 8. Graph of Fruchterman-Reingold.

Finally, the Reingold-Tilford algorithm, developed by John Reingold and Jhon Tilford, is instrumental in arranging tree structures to optimize readability. This algorithm assigns coordinates to each tree node, aligning sibling nodes horizontally and positioning child nodes below parent nodes, fostering a visually comprehensible representation of hierarchical data [51]. Fig. 10 demonstrates the application of this algorithm, configured with 1 as the root vertex.

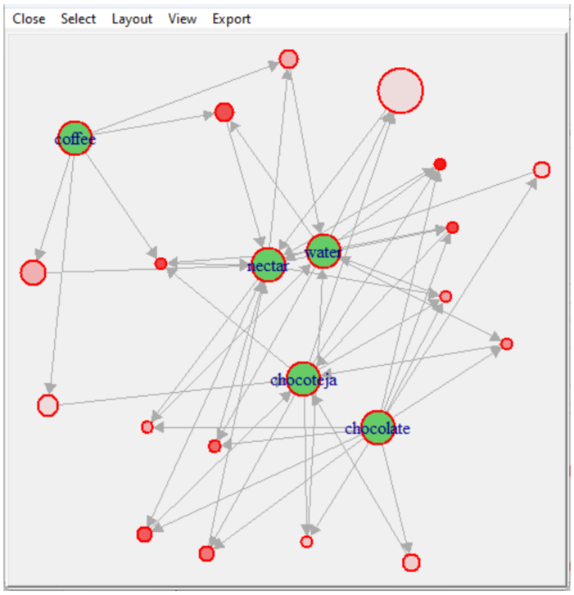


Fig. 9. Graph of Kamada-Kawai.

In Fig. 11, the 17 rules obtained are presented using a visual approach, which provides a graphic and comprehensible representation of the relationships among products. This is essential for interpreting purchase patterns and making strategic decisions in the business and marketing domains. The ability to interactively explore the rules will enable users to gather detailed information about the discovered associations, thereby contributing to a deeper understanding of consumer behavior. In summary, the graphical representations affirm the robustness of the association rules, offering insights into their relationships and highlighting the applicability of diverse algorithms for visualizing these intricate patterns with the dataset. These findings lay a foundation for nuanced interpretations and strategic decision-making.

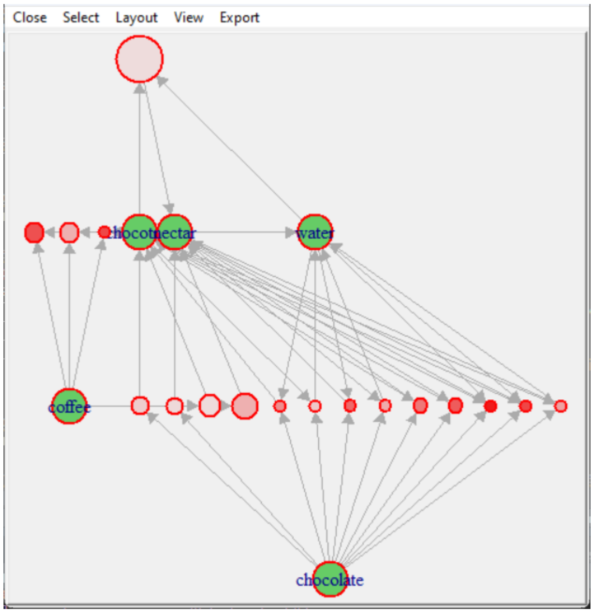


Fig. 10. Graph of Reingold-Tilford.

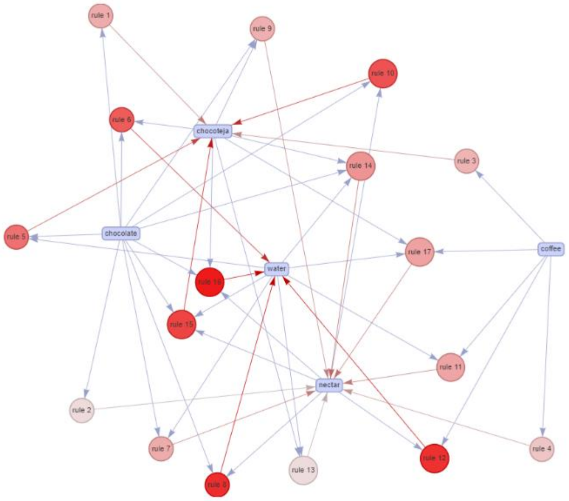


Fig. 11. Graph HTML widget.

In the context of the study, a pivotal challenge confronting marketer lies in augmenting transaction volumes among customers engaged in limited product acquisitions-typically one, two, or three items, a prevalent scenario at CIU-Jaen. Tackling this challenge necessitates the deployment of strategic initiatives, such as flash, strategically amalgamating product displays and promotional information to stimulate impulsive purchases. The subsequent exposition of sales patterns concerning nectar, water, coffee, chocolate and chocoteja, coupled with the discernment of robust association rules, furnishes a valuable foundation for crafting and executing such targeted strategies.

Existing research underscores the affirmative response of customers to well-crafted sales campaigns, particularly in Jaen, a commercial province, where such endeavors hold promising potential for customers attraction and retention. This case study, rooted in the CIU-UNJ market, injects a distinctive dimension into the scholarly discourse by acknowledging and integrating the unique economic and market dynamics inherent to the province of Jaen. Notably, transactions involving three or four products dominated the observe timeframe, a noteworthy insight considering potential marketing budget constraints encountered by institutions within the Jaen market. Despite these constrains, the analysis equips senior management and marketing leaders with the tools to proffer nuanced, tailor-made offering to their customers. Expanding on this point, the identification of frequently co-purchased product combinations empowers companies not only to optimize the physical placement of products within the store but also to devise targeted marketing strategies and product bundles capable of propelling sales.

Nevertheless, it is imperative to acknowledge the constraints imposed by the dataset size and the modest transaction volume averages. Transactions predominantly featuring one or two products limit the scope of the analysis. To enhance the robustness of future studies, it is recommended to use a larger database and the extension of the study duration. This methodological refinement aligns with the pursuit of more objective outcomes, facilitating longitudinal analyses that enable the evaluation of the enduring impacts of strategic marketing decisions on transactional volume and value.

V. Conclusion

This study represents a significant advancement in understanding customer transaction patterns through the application of the Apriori algorithm at CIU-Jaen. By uncovering valuable insights into product associations, the findings inform targeted marketing strategies, discount planning, and direct marketing campaigns, while seamlessly integrating with customer loyalty programs. This holistic approach, embedded within a comprehensive customer relationship management system, enhances the precision and efficacy of marketing initiatives, thereby offering a nuanced understanding of consumer behavior and fostering sustained business growth.

In a broader context, this research offers a nuanced understanding of consumer behavior in the unique market landscape of CIU-Jaen. The association rule identified, based on real transactional data, transcends conventional marketing paradigms, serving as a valuable guide for navigating product placements, promotional efforts, and customer relationship management strategies. As industries grapple with evolving consumer preferences, this study furnishes timely and insightful contributions as a valuable toolset available for strategic decision-making in the domain of marketing and business development.

Looking ahead, future research endeavors could build upon our findings by exploring additional data sources, such as customer feedback and demographic information, to further refine our understanding of consumer behavior. Additionally, investigating the scalability and adaptability of the Apriori algorithm in diverse market contexts could offer valuable insights for practitioners seeking to leverage data-driven approaches in their marketing strategies. Ultimately, by continuously refining our methodologies and insights, we can better anticipate and respond to the evolving dynamics of consumer preferences, driving innovation and growth in the field of marketing and business development.

Acknowledgment

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Automated Detection of Autism Spectrum Disorder Symptoms using Text Mining and Machine Learning for Early Diagnosis

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Abstract—**Autism spectrum disorder (ASD) is a neurological condition whose etiology is still insufficiently understood. The heterogeneity of manifestations makes the diagnosis process difficult. Thus, many children are diagnosed too late, which leads to the loss of precious time that can be used for therapy. A viable solution could be to equip medical staff with modern technologies to detect autism in its early stages. The objective of this research was to investigate, through empirical means, how text mining and machine learning (ML) algorithms can aid in the early ASD diagnosis by identifying patterns and ASD symptoms in text data regarding children's behavior that concerned parents provided. The research involved the design of an innovative technical solution based on text mining for the identification of ASD symptoms in unstructured text data describing children's behavior and the practical implementation of the solution using Rapid Miner. The dataset was created through a controlled experiment with 44 participants, parents of children diagnosed with ASD, who answered questions about their children's (35 boys and 9 girls) behavior. Analysis of the performance of models trained with ML algorithms: Naïve Bayes, K-Nearest Neighbors, Deep Learning and Random Forest revealed that the K-Nearest Neighbors classifier outperformed the other methods, achieving the highest accuracy of 78.69%. Results obtained using text mining and ML demonstrated the feasibility of using parents' narratives to develop predictive models for autism symptoms detection. The achieved accuracy highlights the potential of text mining as an autonomous and time- and cost-effective method for early identification of ASD in children.**

Keywords—Text mining; machine learning; artificial intelligence; assistive technologies; Autism Spectrum Disorder; early diagnosis; screening

I. Introduction

A. Text Mining

Advances in the information technology (IT) industry provide efficient methods for data creation, storage and processing. Global data consumption is growing at an exponential rate, and projections indicate that by 2025, the volume of data used will exceed 180 zettabytes [1]. Today, data means much more than numbers and letters—it includes images, sounds and text. King's research findings [2] indicate that 80% of the world's data is in unstructured format. This statistic highlights the importance of unstructured data processing techniques such as text mining. Text mining is a contemporary concept of computer science that contributes to solving the information crisis by combining data mining (DM), machine learning (ML) and natural language processing (NLP) techniques.

B. Medical Text Mining

The scientific community explored new horizons for the applicability of text mining and understood the utility of this technology in the medical field [3], [4], [5]. The healthcare industry collects enormous amounts of unstructured text information such as patient data, clinical test results, doctor observations and notes. These records, which are typically stored in electronic format, have the potential to enhance the standard of medical treatment by supporting physicians in making well-informed decisions. However, most of this valuable information is unused. One reason for ignoring this data is the lack of appropriate technological tools for processing the large volume of unstructured data. Contemporary advances in IT have contributed to the development of artificial intelligence (AI) algorithms that have facilitated the growth of medical text mining. The term "medical text mining" refers to methods of processing and extracting knowledge from medical text. This area of research combines ideas and techniques from linguistics and health informatics (HI). As emphasized by Dalianis [6], who analyzed the applicability of text mining in the clinical field, text mining is used for NLP, classification, clustering, information extraction (IE) and information retrieval (IR).

C. Autism Spectrum Disorder

Autism Spectrum Disorder (ASD) is defined as a complex neurological and developmental disease by the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) that is characterized by difficulties with communication and social interaction [7]. The ASD prevalence is estimated at 1 in 100 children according to World Health Organization (WHO) [8]. The high incidence raises a wake-up call to improve the capacity of medical institutions to treat ASD and other developmental disabilities.

D. Challenges of Early Autism Spectrum Disorder Diagnosis

Early autism diagnosis and therapeutic interventions have been reported to be important for achieving satisfactory clinical progress [9]. Conventional approaches to ASD diagnosis involve a comprehensive clinical evaluation and developmental screening with standardized tests, and interviews with psychologists and medical specialists such as Autism Diagnostic Observation Schedule (ADOS) [10], Autism Diagnostic Interview Revised (ADI-R) [11] and Diagnostic

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Interview for Social and Communication Disorder (DISCO) [12]. However, due to the heterogeneity of ASD, the presence of false positive results remains a challenge for clinicians [13]. In addition, clinical examinations are time-consuming and negatively influence the patient behavior because patient is not in the home environment and is surrounded by unfamiliar people and these stimuli may be triggers for crisis-value behaviors.

E. Automated Detection of Autism Spectrum Disorder Symptoms Using Text Mining and Machine Learning

New technologies can help doctors and families who suspect their child may have autism in screening and diagnosis. Text mining provides capabilities to analyze large amounts of unstructured text data related to a child's behavior, development, and interaction.

The present research study findings revealed that text processing algorithms can recognize ASD-specific symptoms in semi-structured screening texts and unstructured texts such as parents' narratives. This scalability holds substantial advantages for doctors, providing them with tools based on text mining technology that can analyze data and flag risk factors or markers of autism. By integrating text mining into diagnostic procedures, healthcare professionals and parents can benefit from early detection of autism symptoms, accurate analysis, and improved support for children with ASD. From this perspective, the contributions of our study are:

- The design of an innovative technical solution based on text mining to identify ASD symptoms in unstructured text data that describes the child's behavior and the practical implementation of the solution that involved a controlled experiment with 44 participants, parents of children diagnosed with ASD.
- Empirical analysis of the accuracy of models trained to identify ASD symptoms in unstructured text data with Naïve Bayes, K-Nearest Neighbors, Deep Learning, Radom Forest ML algorithms.
- Outline of implications for employing text mining in the design and development of healthcare technologies for ASD diagnosis.

F. Paper Structure

The structure of this paper is organized to provide a comprehensive understanding of the design and implementation of the automated ASD symptom detection process using text mining and ML. In the introduction section, we outline the context and highlight the importance of research for early autism diagnosis. Section II describes the methodology used to conduct the research and collect information from parents of children with ASD. Section III brings an in-depth analysis of the results obtained, emphasizing the advantages and limitations. Finally in Section IV, we present the conclusions and outline directions for future research.

II. Materials and Methods

A. Research Questions

The present study's aim was to investigate, through empirical means, how text mining and machine learning algorithms can aid in the early ASD diagnosis by detecting patterns and ASD symptoms in text data regarding children's behavior that concerned parents provided. To address the topic of interest two research questions were formulated and are presented in Table I.

TABLE I. Research Questions

ID	*Research Question (RQ)*
RQ_1	Can text mining be used for detection of ASD symptoms in unstructured text data describing children's behavior?
RQ_2	What are the empirical results of applying text mining and ML algorithms in terms of accuracy in correctly detecting ASD symptoms?

B. Research Participants

The research of Okoye et al. [14] emphasizes the importance of screening in early childhood, between the ages of 18 and 24 months, to achieve positive results in the therapeutic recovery process. Therefore, the premature age of the children and the reduced reading and writing abilities, at this stage of life, determined the involvement of adults in the experiment. 44 parents of children diagnosed with ASD voluntarily participated in the experiment, of which 27 came from the urban environment and 17 from the rural environment, as represented in Fig. 1.

Autism is not equally distributed between genders, with a male-to-female ratio of 4:1 [15]. Approximately the same gender ratio is also encountered in the children participating in the experiment, 35 boys and 9 girls, as indicated in Fig. 2. It is important to understand the gender distribution because symptoms in girls may manifest differently than in boys, thus leading to under diagnosis of ASD in girls [16].

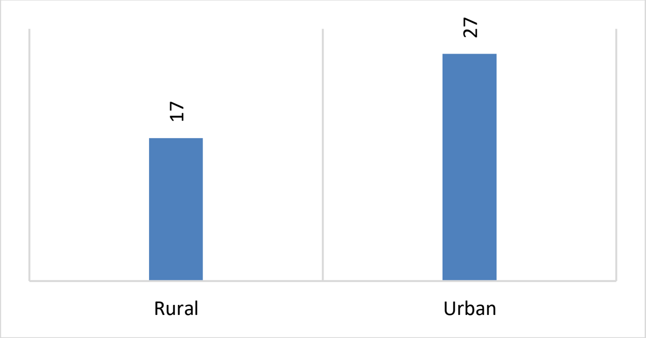


Fig. 1. The distribution of participants according to their residence.

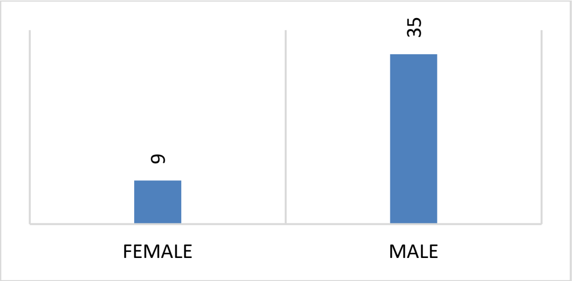


Fig. 2. The gender distribution of children with ASD participating in the experiment.

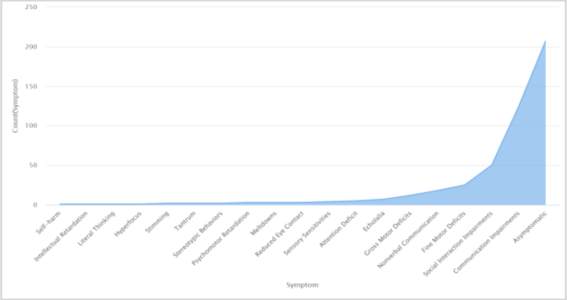


Fig. 3. The quantitative distribution of labels in the dataset.

C. Research Methodology

Following ethics committee approval, participants were invited to answer questions about their child's behavior using the web-based version of Google Forms as instrument. Questions were formulated based on the ASD diagnostic criteria described in DSM-5 [17]. The raw data collected from the participants was analyzed and labeled. The labeling scheme contains 19 labels of which 18 labels represent symptoms specific to autism and one special label "Asymptomatic" which indicates the absence of ASD symptoms. Fig. 3 highlights the quantitative distribution of labels in the dataset. It is noted that the label "Asymptomatic" is the most frequently encountered. This tendency is explained by the fact that the ASD symptom was labeled only in situations where the answer provided by the parent was sufficiently detailed and descriptive to identify that manifestation.

D. Architecture of Technical Solution for Automated Detection of Autism Spectrum Disorder Symptoms using Text Mining and Machine Learning

Diagnosing ASD is a difficult task because the etiology and factors that cause autism are unknown. In addition, the large spectrum of symptoms and the lack of an accurate medical test, such as a blood test, complicate the diagnosis process. Fig. 4 illustrates the conventional diagnosis process, which involves the human factor, represented by the doctor. The doctor analyzes patient biological parameters and applies screening tests and psychological strategies to identify ASD symptoms. The research carried out by Akinnusotu et al. [18] indicate that demanding work conditions affect the psychological state of medical personnel, having an impact on the diagnoses and the effectiveness of recommended treatments. Augmentation of medical workers with modern technologies can be a viable solution in combating burnout. Fig. 5 shows the automated ASD diagnosis process that eliminates the human factor and introduces text mining and ML algorithms to discover autism symptoms in patient data.

The architecture of technical solution for automated ASD symptoms detection in unstructured text data involves complex stages to extract relevant information and build a model capable of recognizing symptoms associated with autism. The stage is inspired by knowledge discovery in text (KDT), a documented research methodology. Fig. 6 present the technical solution implemented using RapidMiner Studio 10.2.

1) Data preprocessing: The data preprocessing is an essential stage in the identification process of ASD symptoms and requires collaboration with qualified medical professionals to draw conclusions about the health status of the participants. These conclusions should be reflected in the labels associated with the text data.

In this stage, records from the dataset that are incomplete and do not provide qualitative information must be removed.

2) Model training: The data preprocessed in the previous phase should be used to train a machine learning model capable of recognizing the ASD symptoms in text data describing the behavior of the child whose parent's suspect autism.

3) Model testing: The model testing stage consists of providing a test dataset as input to the trained model and calculating the performance indicators.

4) Results analysis: The results analysis consists in evaluating the performance of the trained model using the metrics computed in the previous stage, such as accuracy and classification error. Depending on the evaluation results, the model parameters can be adjusted and new machine learning algorithms can be explored.

The automated process of ASD symptoms detection in unstructured text data is empirical and needs to be refined iteratively by experimenting with feature representation, adjusting preprocessing steps and applied machine learning algorithms.

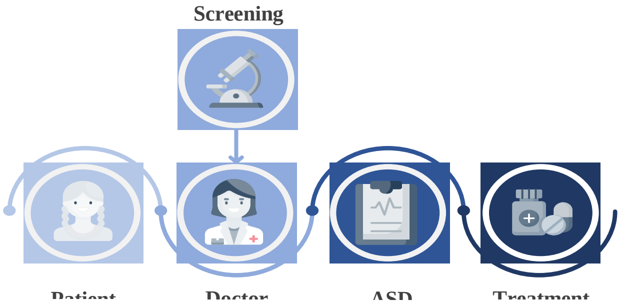


Fig. 4. Conventional ASD diagnosis process.

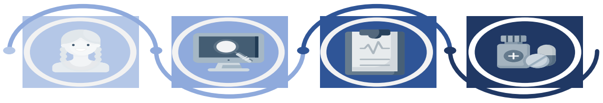
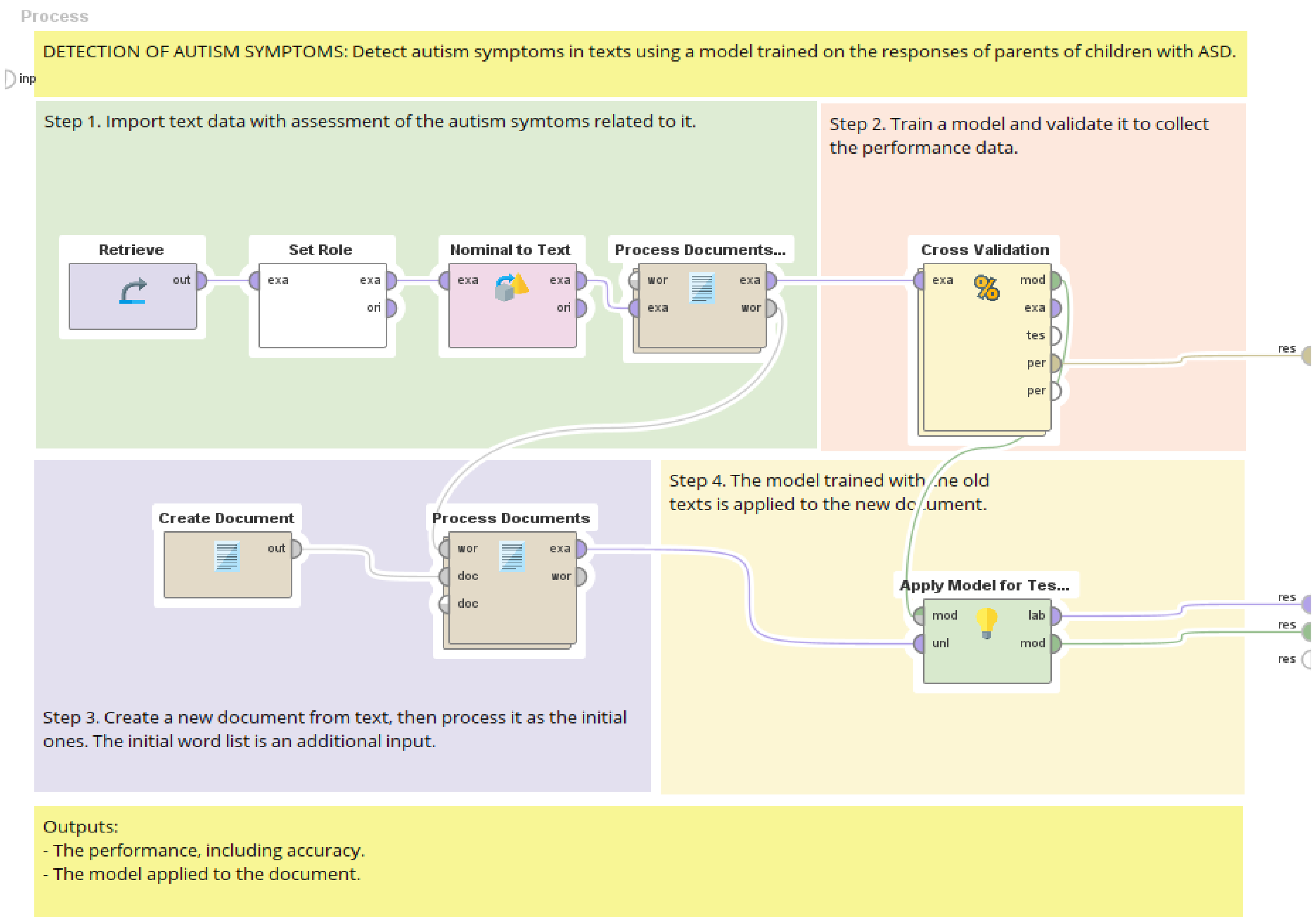


Fig. 5. Automated ASD diagnosis process.



DETECTION OF AUTISM SYMPTOMS: Detect autism symptoms in texts using a model trained on the responses of parents of children with ASD.

Step 1. Import text data with assessment of the autism symtoms related to it.

Step 2. Train a model and validate it to collect the performance data.

Step 3. Create a new document from text, then process it as the initial ones. The initial word list is an additional input.

Step 4. The model trained with the old texts is applied to the new document.

Outputs:
- The performance, including accuracy.
- The model applied to the document.

Fig. 6. Automated ASD symptoms detection process.

E. Text Mining

In text mining, the most influential step is text preprocessing, as it prepares the data for mining. Text preprocessing involves cleaning and transforming raw text data into a suitable format for analysis. In the present context, the Text Processing package was used to preprocess the dataset, with a focus on removing words from parents' responses to the questions that did not make a significant contribution to meaning. This approach aimed not only to improve the quality of the extracted information, but also to reduce the size of the vocabulary, thus contributing to the efficient management of the computational complexity of the dataset. Several methods were applied during text preprocessing: capitalization, tokenization, filter stopwords, stemming, n-Grams and term weighting.

1) Capitalization: Bringing all words to a standardized form, such as converting all letters to uppercase or lowercase, to ensure consistency in textual analysis. Capitalization helps reduce the amount of distinct information that ML algorithms have to process. In ADS symptoms detection process the text data was converted a to lowercase (see Fig. 7).

Example

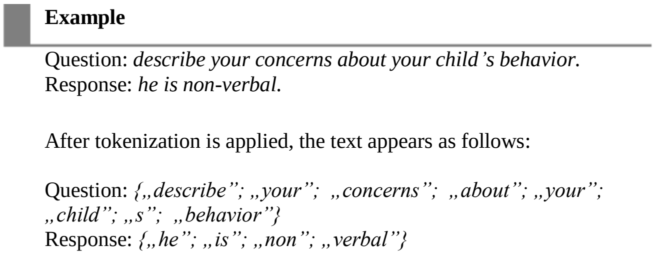
Question: *Describe your concerns about your child's behavior.*
Response: *He does not interact with the other children.*

After capitalization is applied, the text appears as follows:

Question: *describe your concerns about your child's behavior.*
Response: *he does not interact with the other children.*

Fig. 7. Example of applying capitalization to a record from the dataset.

2) Tokenization: Breaking down the text into meaningful element, known as tokens, such as words or phrases, to facilitate manipulation and subsequent analysis [19]. Tokenization is language dependent and involves the removal of punctuation marks from the text. The example in Fig. 8 shows the result of applying tokenization to a record from the dataset. As can be noticed this technique does not take into account words composed by the use of hyphens as "non-verbal". For this reason, engineers must pay attention when using the tokenization technique.



Example

Question: *describe your concerns about your child's behavior.*
Response: *he is non-verbal.*

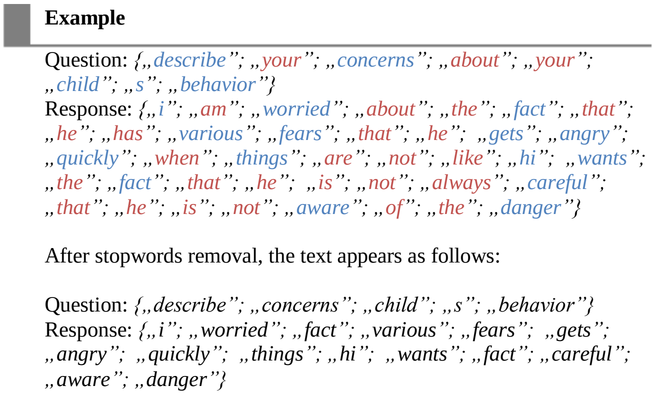
After tokenization is applied, the text appears as follows:

Question: *{„describe"; „your"; „concerns"; „about"; „your"; „child"; „s"; „behavior"}*
Response: *{„he"; „is"; „non"; „verbal"}*

Fig. 8. Example of applying tokenization to a record from the dataset.

3) Filter stopwords: Exclusion of frequently used or rare words called stopwords to reduce the vocabulary size and focus on key words. Stopwords usually are prepositions, conjunctions, auxiliary verbs and pronouns that do not bring significant contribution to the definition of information.

In ADS symptoms detection process was used the Filter Stopwords operator which has a built-in list of stop words for the English language and contains words such as "at", "etc", "if", "or", etc. The Fig. 9 demonstrates the result of filtering stopwords from a parent's response describing concerns about the child's behavior. Words such as "am", "the", "of", "that", "about", "he", "has", "when", "not" and "always" have been removed from the original text, keeping the meaning intact.



Example

Question: *{„describe"; „your"; „concerns"; „about"; „your"; „child"; „s"; „behavior"}*
Response: *{„i"; „am"; „worried"; „about"; „the"; „fact"; „that"; „he"; „has"; „various"; „fears"; „that"; „he"; „gets"; „angry"; „quickly"; „when"; „things"; „are"; „not"; „like"; „hi"; „wants"; „the"; „fact"; „that"; „he"; „is"; „not"; „always"; „careful"; „that"; „he"; „is"; „not"; „aware"; „of"; „the"; „danger"}*

After stopwords removal, the text appears as follows:

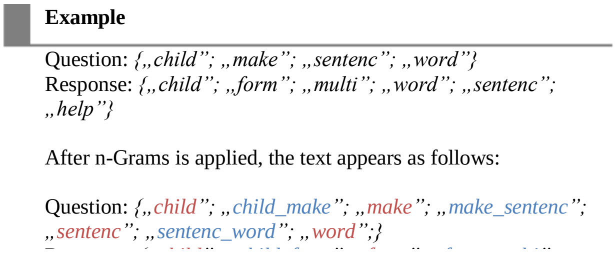
Question: *{„describe"; „concerns"; „child"; „s"; „behavior"}*
Response: *{„i"; „worried"; „fact"; „various"; „fears"; „gets"; „angry"; „quickly"; „things"; „hi"; „wants"; „fact"; „careful"; „aware"; „danger"}*

Fig. 9. Example of applying filter stopwords to a record from the dataset.

4) Stemming: In linguistic morphology stemming is the normalization process of reducing inflected, derived words to their basic form, the root. The root is the part of a word that is common to all its inflected variants. The process of stemming involves removing prefixes or suffixes. To achieve this we used Porter's stemming algorithm. Porter's stemming algorithm removes suffixes from a word, from the English language, to obtain its root [20]. The algorithm consists in marking the consonants in the word with the letter C and the vowels with the letter V. Thus all words can be represented by the Eq. (1).

$$[C]VCVC \ldots [V] \tag{1}$$

5) n-Grams: n-Grams is a text preprocessing method mainly used for feature extraction. An n-Gram is a series of consecutive tokens of length *n* used to capture contextual information and improve the understanding of the text. Fig. 10 shows the result of applying n-Gram to a record from the dataset.



Example

Question: *{„child"; „make"; „sentenc"; „word"}*
Response: *{„child"; „form"; „multi"; „word"; „sentenc"; „help"}*

After n-Grams is applied, the text appears as follows:

Question: *{„child"; „child_make"; „make"; „make_sentenc"; „sentenc"; „sentenc_word"; „word";}*

Fig. 10. Example of applying n-Grams to a record from the dataset.

6) Term weighting: Weighting is the process by which the importance of term in the text dataset is quantified. Each term is associated with a value called a weight, which symbolizes how indispensable it is for the text mining process.

In the automated ADS symptoms detection process, Term Frequency - Inverse Document Frequency (TF-IDF) was used to determine the weights. TF-IDF is a statistical measure intended to quantify the importance of a word in a document or corpus. TF-IDF aims to reduce the influence of common words on the model [21].

F. Machine Learning

ML is a subset of AI that focuses on developing systems capable of learning and making decisions without being explicitly programmed. The automated detection of ASD symptoms in text data involved the exploration of four ML algorithms suitable for training a classification model:

- Naïve Bayes (NB) - The NB classifier is a supervised learning algorithm based on Bayes theorem. The algorithm calculates the probability of each class (labels) and then chooses the class with the most likely probability [22].
- K-Nearest Neighbors (k-NN) - The k-NN is a non-parametric algorithm that operates by finding the K nearest neighbors to a given data point based on a metric such as Euclidean distance. The class or value of the data point is then determined by the average of its K neighbors [23].
- Deep Learning (DL) - The DL algorithm is based on a multi-layer artificial neural network that is trained with stochastic gradient descent using back-propagation. The network can contain a large number of hidden layers consisting of neurons with tanh, rectifier and maxout activation functions [24].
- Radom Forest (RF) - The RF is a ML algorithm that uses an ensemble of decision trees to make predictions. Each decision tree is trained on a different data subset, and the predictions of all trees are averaged to produce the final prediction [25].

In order to identify the algorithm that produces the best performing model for automated detection of ASD symptoms a cross-validation was implemented. Cross-validation is a technique used in ML for assessing and comparing learning algorithms by dividing data into two segments: one used to train a model and the other used to validate the model [26].

The performance evaluation involved calculation of the metrics: accuracy, classification error, Cohen's kappa coefficient, and weighted mean recall. To determine these metrics the confusion matrix was used. Confusion matrix is a performance measurement where the columns represent the predicted values and the rows represent the actual values. According to Kulkarni et al. [27] confusion matrix contains the following elements:

- True Positive (TP): Instances where the model correctly predicted the positive class.
- True Negative (TN): Instances where the model correctly predicted the negative class.
- False positive (FP): Instances where the model incorrectly predicted the positive class.
- False Negative (FN): Instances where the model incorrectly predicted the negative class.

Using TP, TP, FP, FN, and Observed Accuracy (OA) and Expected Accuracy (EA) the follow metrics were determined:

- Accuracy - The accuracy represents the percentage of correct predictions out of the total predictions and is calculated using (2).

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (2)$$

- Classification error - The classification error represents the percentage of incorrect predictions and is calculated using (3).

$$\text{Classification error} = (FP + FN)/(TP + FP + FN + TN) \quad (3)$$

- Cohen's kappa coefficient – The kappa coefficient is a robust statistical metric that measures the observed versus expected accuracy and is calculated using (4).

$$Cohe's\ kappa\ coefficient = (OA - EA)/(1 - EA) \quad (4)$$

- Weighted mean recall – The weighted mean recall is calculated by taking the weighted mean of negative recall in Eq. (5) and positive recall in Eq. (6).

$$Negative\ recall = TN/(TN + FP) \quad (5)$$

$$Positive\ recall = TP/(TP + FN) \quad (6)$$

III. Results

A. Results for RQ$_1$

Each child with ASD has a unique behavior pattern and level of severity. Some children exhibit signs of autism in early childhood, while others may develop typically in the first few months or years of life, but then suddenly become withdrawn, aggressive, or lose previously acquired linguistic abilities [28]. Fig. 11 presents most common ASD symptoms displayed by children of study participants. The process of automated detection of ASD symptoms in unstructured text data, representing parents' responses to questions about the behavior of their children, was empirical and involved iterative refinement and experimentation with different feature representations and ML algorithms. The results of the performance metrics analysis revealed that the model trained using the k-NN algorithm produces a high accuracy of 78.69% and is feasible for ASD symptoms detection. As we progressed in exploring text mining technology in the ASD field, we identified several important implications for future research:

- The efficacy of the text mining process is contingent upon the size of the data. Identifying ASD symptoms proved to be more challenging in the concise responses provided by parents.
- The text mining technique is negatively influenced by figures of speech such as metaphors, irony, and euphemism and can introduce ambiguity in the interpretation of language. Future research should focus on addressing this limitation by improving algorithms so that they handle figures of speech more effectively.
- The limited diversity of the dataset requires caution in generalizing findings. Future research should include more diverse linguistic expressions and cultural contexts to increase the model's applicability.

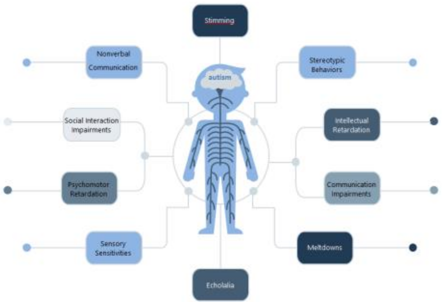


Fig. 11. Most common ASD symptoms exhibited by children of study participants.

The automated detection of ASD symptoms creates opportunities for future research that can further develop healthcare technologies using text mining and ML for autism diagnosis. Automating the symptom identification process provides an efficient alternative to manually reviewing texts written by parents in questionnaires, messages and videos recorded during medical examinations. This efficiency is important for widespread implementation.

B. Results for RQ$_2$

The results obtained from the computation of the accuracy are presented in Fig. 12. The k-NN algorithm outperformed other methods, achieving the highest accuracy of 78.69%. In contrast, the RF algorithm yielded less favorable outcomes, with an accuracy rate of only 54.25%.

The outcomes derived from the calculation of the classification error are depicted in Fig. 13. Analysis of the classification error revealed that k-NN had the lowest error rate at 21.31%, while RF registered the highest classification error of 45.75%.

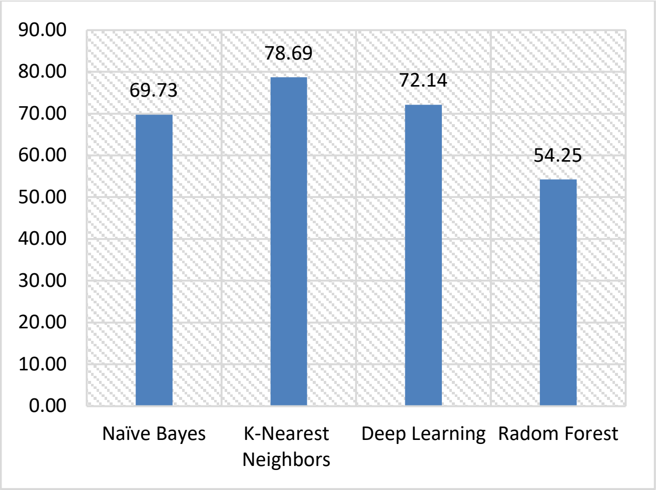


Fig. 12. The accuracy generated by models trained for the automated detection of ASD symptoms.

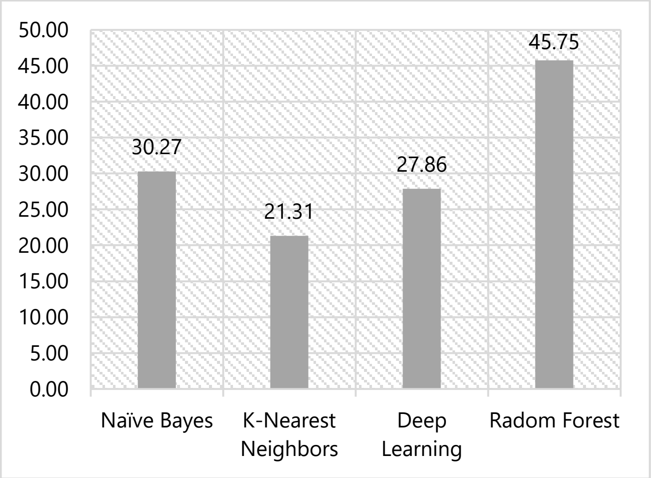


Fig. 13. The classification error generated by models trained for the automated detection of ASD symptoms.

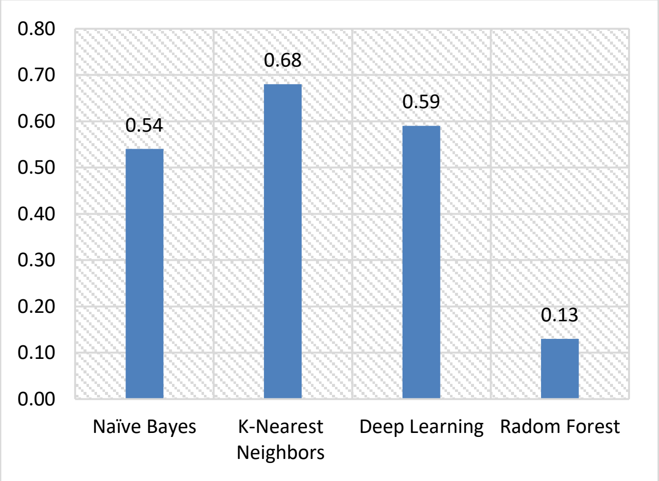


Fig. 14. The Cohen's kappa coefficient generated by models trained for the automated detection of ASD symptoms.

The results obtained after computing Cohen's kappa coefficient are presented in Fig. 14. This coefficient is useful in distinguishing correct predictions that occur by chance and a value below 0.40 is considered unsatisfactory. k-NN demonstrates the stronger association with a kappa coefficient of 0.68.

The results obtained from the computation of the weighted mean recall are presented in Fig. 15 and contribute to the conclusion that k-NN and DL are algorithms that produce more effective models for automated ASD symptoms detection.

Fig. 16 presents the result of testing the model trained using k-NN on a text data that was labeled with the "Communication Impairments" symptom.

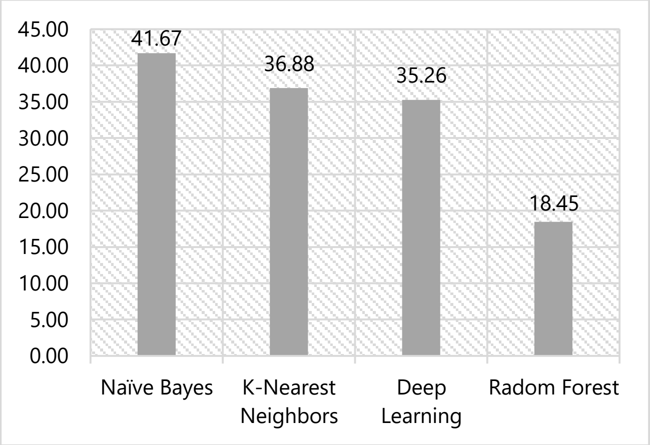
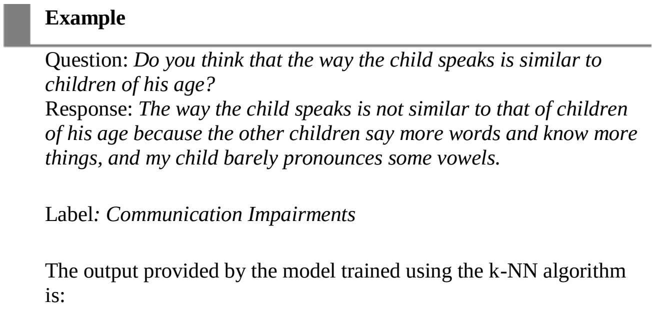


Fig. 15. The weighted mean recall generated by models trained for the automated detection of ASD symptoms.



Example

Question: *Do you think that the way the child speaks is similar to children of his age?*
Response: *The way the child speaks is not similar to that of children of his age because the other children say more words and know more things, and my child barely pronounces some vowels.*

Label*: Communication Impairments*

The output provided by the model trained using the k-NN algorithm is:

Fig. 16. Example of testing the model trained with the k-NN algorithm.

It can be observed from the example that through the application of text mining, the ASD symptom "Communication Impairments" was correctly identified. This is impressive, considering that the text included words and expressions that might have posed a challenge for the trained model, such as "know more" or "say more words", which could be associated with positive behavior and the absence of autism markers. This promising result may have significant implications for text mining integration into applications for autism detection.

IV. Conclusions

Text mining is an efficient IT concept for extracting knowledge from text data. The current study explored text mining techniques and methods in a practical way and focused on analyzing text data provided by 44 parents of children diagnosed with ASD, trying to identify linguistic patterns and indicators that may contribute to the detection of ASD symptoms. The data collected from the participants underwent labeling, using a scheme that comprises 19 labels. Of these, 18 correspond to ASD symptoms, while the remaining label is designated as “Asymptomatic”. The dataset was employed to train four predictive models using ML algorithms, including NB, k-NN, DL and RF.

Results obtained through text mining and ML demonstrated the feasibility of using parents’ narratives to develop predictive models for autism symptoms detection. The achieved accuracy of 78,69% highlights the potential of text mining as an autonomous and time- and cost-effective method for the early identification of ASD in children. However, it is important to mention that the ambiguous nature of language can pose challenges in the exploration process and for this reason a representative and diverse training dataset must be employed.

Future research could address the identified limitations and develop healthcare technologies based on the process of detection of ASD symptoms in unstructured text data designed in this study.

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A Novel Inter Patient ECG Arrhythmia Classification Approach with Deep Feature Extraction and 1D Convolutional Neural Network

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***Abstract*—The World Health Organization (WHO) sheds light on the escalating prevalence of heart diseases, foreseeing a substantial rise in the years ahead, impacting a vast global population. Swift and accurate early detection becomes pivotal in managing severe complications, underscoring the urgency of timely identification. While Ventricular Ectopic Beats (V) might initially be considered normal, their frequent occurrence could serve as a potential red flag for progressing to severe conditions like atrial fibrillation, Ventricular Tachycardia, and even cardiac arrest. This accentuates the need for developing an automated approach for early detection of cardiovascular diseases (CVD). This paper presents a novel method to classify arrhythmias. Leveraging the Wavelet Scattering Transform (WST) to extract morphological features from Electrocardiogram heartbeats (ECG), these features seamlessly integrate into a 1D Convolutional Neural Network (CNN). The CNN is finely tuned to distinguish between V, Supraventricular Ectopic Beats (S), and Non-Ectopic Beats (N). Our model's performance surpasses state-of-the-art models, boasting precision, sensitivity, and specificity of 94.56%, 97.26%, and 99.54% for V, and 99.25%, 98.65%, and 93.26% for N. Remarkably, it achieves 68.01% precision, 77.75% sensitivity, and 99.14% specificity for S.**

Keywords*—*Electrocardiogram (ECG); Cardiovascular Diseases (CVD); Wavelet Scattering Transform (WST); Convolutional Neural Network (CNN)

I. Introduction

According to the World Health Organization (WHO), cardiovascular diseases (CVD) stand as the foremost cause of global mortality, contributing to approximately 17.9 million deaths annually. This staggering toll is predominantly attributed to coronary heart disease, encompassing heart attacks, and Cerebrovascular illnesses, including strokes, which collectively account for 80% of these fatalities. The demographic most vulnerable to these health challenges comprises individuals in their middle and elderly years [1]. Clinical research in the preceding century has significantly advanced to facilitate the early detection of CVD. During the historical period when the electrical nature of the heart was widely acknowledged, a notable challenge existed due to the absence of tools for its systematic study. It is noteworthy that the exploration of electricity in the medical domain had commenced nearly two centuries before Einthoven's pivotal contributions. Pioneers such as: Gilbert with his work "De Magnete" in 1600, Bacon through "Novum Organum" in 1620, and Browne who coined the term electricity in the mid-seventeenth century within "Pseudodoxia Epidemica" in 1646, had laid the foundation for understanding electrical phenomena in the context of medicine.

Despite this early groundwork, it was only with Einthoven's groundbreaking efforts that a tangible method, namely the EKG or ECG, was developed to specifically delve into the intricate electrical dynamics of the heart [2]. In the year 1893, Einthoven not only introduced the term "electrocardiogram" but also demonstrated notable advancements by enhancing the electrometer. His significant contributions included the introduction of a correction formula, a pivotal innovation that enabled the differentiation of five distinct deflections [3-4]. These deflections, denoted by the names PQRST, were assigned based on the Cartesian nomenclature.

Comprising P, QRS, and T waves, along with an array of intervals, the electrocardiogram (ECG) serves as a comprehensive diagnostic tool. This intricate waveform not only facilitates the analysis of fundamental parameters such as heart rate but also provides invaluable insights into the intricate conditions and potential risks associated with the heart's functionality [5].

By examining these distinctive components and intervals, clinicians can glean a nuanced understanding of cardiac health, enabling them to address and mitigate potential issues proactively. Determining the signal's classification into the normal range or otherwise relies crucially on assessing the amplitude measured in millivolts and the intervals expressed in milliseconds [6].

Sinus rhythm, denoting the typical heart rhythm, is characterized by the orchestrated propagation of triggering impulses originating from the sinoatrial node. This synchronized transmission extends seamlessly throughout the four chambers of the heart, ensuring a harmonious and coordinated cardiac activity [7]. The underlying cause of Cardiac arrhythmia (ARR) stems from the disruption of proper electrical impulses that orchestrate the coordinated beats of the heart (too slow or too fast) [7]. It is noteworthy that certain ARRs, if left unaddressed, pose a serious threat, potentially leading to sudden cardiac death. Hence, understanding and addressing these dangerous arrhythmic conditions becomes paramount in safeguarding cardiovascular health.

ARRs encompassing four prevalent types: extra beats, supraventricular tachycardia, ventricular ARRs, and brady-arrhythmias [8-9]. Premature (extra) beats include both premature atrial contractions (PAC) and premature ventricular contractions (PVC). Supraventricular ARRs initiate in the atria, characterized by elevated heart rates, they include atrial fibrillation (AF), atrial flutter, paroxysmal supraventricular tachycardia (PSVT), and Wolff-Parkinson-White syndrome. Within the realm of ventricular ARRs lie Ventricular flutter, Ventricular tachycardia (VT), and Ventricular fibrillation (VF).

These potentially life-threatening conditions necessitate immediate intervention, often requiring the prompt administration of a defibrillator shock to safeguard and preserve life. Heart block, a condition that can manifest in the atrioventricular node or the HIS Purkinje system, it leads to an irregular slowed heartbeat, potentially necessitating the use of a pacemaker for treatment. The condition is observed on either the left or right side of the ventricles, identified as right bundle branch block (RBBB) or left bundle branch block (LBBB).

Precise interpretation of ECG signals holds the potential to avert the progression of chronic heart conditions to irreversible stages. However, the manual interpretation and analysis of ECG pose a formidable challenge [10-11]. Moreover, beyond the challenge of manual interpretation, the analysis of long-term ECG signals is a time-intensive endeavor, susceptible to human errors that may compromise the accuracy of assessments [12-13-14, 15].

In recent decades, researchers have responded to the challenges by developing automated models aimed at the detection and in-depth analysis of long-term ECG signals. This innovative approach not only addresses the limitations associated with manual interpretation but also heralds a paradigm shift in enhancing the efficiency and accuracy of cardiac signal assessment over extended periods. These techniques solely rely on advancements in machine learning and deep learning [16-17, 18], which have seen significant progress in recent years, thanks to the continuous development of computer systems and technology.

In the ensuing sections, relevant literature was explored, outlining automated heartbeat classification models. Subsequently, in the methodology, the meticulous preparation and processing of our data were unfolded, the method employed for feature extraction was elucidated, and a comprehensive explanation of the classifier utilized was provided; including its parameters, along with the evaluation metrics employed to assess the efficacy of our proposed model.

Moving forward, the results and discussion section expounded on our findings, drawing comparisons with state-of-the-art systems. Lastly, the conclusion section summarized our results, highlighted the limitations inherent in this study, and proposed avenues for future research to address these constraints.

II. Related Works

A. *Methodology Overview in Previous Studies*

This section introduces state-of-art automated inter-patient ECG heartbeat classification models, adhering to the Association for the Advancement of Medical Instrumentation (AAMI) recommendation [19]. These models categorize ECG heartbeats into five types according to the AAMI standard: Normal (N), Supraventricular ectopic beats (S), Ventricular ectopic beats (V), Fusion beats (F), and Unknown beats (Q), as outlined in Table I.

TABLE I. AAMI Heartbeat Classes

AAMI Classes	**MIT-BIH heartbeats**
N	Normal (N)
	Right bundle branch block beats (RBBB)
	Nodal (junctional) escape beats (j)
	Left bundle branch block beats (LBBB)
	Atrial escape beats (e)
S	Aberrated atrial premature beats (a)
	Atrial premature contraction (A)
	Supraventricular premature beats (S)
	Nodal (junctional) premature beats (J)
V	Premature Ventricular contraction (PVC)
	Ventricular escape beats (E)
	Flutter wave (!)
F	Fusion of ventricular and normal beat (F)
Q	Paced beat (/)
	Fusion of paced and normal beat (f)
	Unclassified beat (Q)

Sellami et al. [20] introduced a deep CNN, leveraging state-of-art deep learning techniques for precise heartbeat classification. They advocated for a batch-weighted loss function to effectively address class imbalances, wherein the loss weights dynamically adjust based on the changing class distribution in each batch. Additionally, they proposed the utilization of multiple heartbeats to enhance the classification of the five heartbeat classes. The evaluation of their proposed approach on inter-patient data from the MIT-BIH arrhythmia database yielded results, their model achieving an accuracy, precision, sensitivity, and specificity of 88.34%, 45.25%, 90.90%, and 88.51%, respectively.

Li et al. [21] employed the overlapping segmentation method to divide ECG signals from the MIT-BIH database into 5-second segments, addressing class imbalances by re-labeling these segments. Subsequently, discrete wavelet transform (DWT) was applied for denoising, and a deep residual CNN was employed for ARR classification. They incorporated the focal loss function. Their proposed method demonstrated a sensitivity, precision, and specificity of 94.54%, 93.33%, and 80.80% for class N. For class S, the model achieved 35.22% sensitivity, 65.88% precision, and 98.83% specificity, while for class V, the method exhibited 88.35% sensitivity, 79.86% precision, and 94.92% specificity.

Garcia et al. [22] presented an innovative approach wherein they proposed an ECG representation based on vectorcardiogram, termed temporal vectorcardiogram. They employed a complex network for feature extraction and fine-tuned an SVM classifier using the particle swarm optimization algorithm. The results of their approach, applied to inter-patient analysis on the MIT-BIH arrhythmia database, demonstrated a precision of 53% for class S and 87.3% for class V.

Wang et al. [23] introduced an automated ECG classification method that relies on Continuous Wavelet Transform (CWT) and CNN. The CWT is employed to decompose ECG signals, yielding distinct time-frequency components. Subsequently, the CNN is utilized to extract features from the 2D-scalogram composed of these time frequency components. 4 RR interval features are extracted and combined with the CNN features and inputted into a fully connected layer. The proposed model demonstrated a sensitivity of 99.04%, precision of 98.04%, and specificity of 87.95% for class N. For class S, the model achieved a sensitivity of 70.75%, precision of 77%, and specificity of 99.51%. Additionally, for class N, the sensitivity, precision, and specificity were 94.35%, 95.32%, 99.45%, respectively.

Takalo et al. [24] introduced a method for inter-patient ECG heartbeat classification, leveraging a deep CNN. Their proposed approach demonstrated commendable performance, achieving a sensitivity of 92% and precision of 97% for class N. Additionally, for class S, the method attained a sensitivity of 62% and precision of 56%. Finally, in the case of class V, their approach yielded a sensitivity of 89% and a precision of 51%.

Junaid et al. [25] proposed a 1D self-organized operational neural network for the inter-patient classification of ECG heartbeats from the MIT-BIH arrhythmia database. Their method exhibited an overall accuracy of 95.99% across: N, S, and V. Specifically, for class N, the proposed method achieved a sensitivity of 98.48%, precision of 97.39%, and specificity of 76.82%. In the case of class S, they attained a sensitivity of 44.01%, precision of 64.50%, and a specificity of 99.01%. Lastly, for class V, the method demonstrated a sensitivity of 92.96%, precision of 89.62%, and a specificity of 99.22%.

He et al. [26] introduced a new method, multi-level unsupervised domain adaptation framework (MLUDAF), for diagnosing ARRs. They used the spatial pyramid pooling residual (ASPP-R) module to extract spatio-temporal features and employed the graph convolutional network (GCN) module for data structure features. In domain adaptation, they aligned domains, semantics, and structures. Testing on MIT-BIH yielded a 96.8% overall accuracy. Notably, the model achieved 97.8% sensitivity and 99.5% precision for N class, 89.2% sensitivity and 90.4% precision for V class, and 90.2% sensitivity and 53.2% precision for S class.

It's crucial to highlight those previous studies have largely overlooked classes F and Q due to their minimal representation (less than 1%) in the MIT-BIH dataset. As these classes make an insignificant contribution to overall performance, they were excluded. Including them in model training would lead to an imbalanced dataset, adversely impacting classification results. Thus, this research focuses exclusively on classes N, S, and V for a more effective analysis.

B. Limitations and Gaps in Previous Studies

It's noteworthy that Wang et al. [23] achieved the best results in distinguishing N, S, and V classes, with an overall accuracy of 97.68%. However, their approach fell short, particularly in classifying S with a sensitivity below 70.75% and limited precision at 77%. Similar limitations were observed in class V, where sensitivity did not exceed 94.35%, and precision reached only 95.32%. This underscores the need for a novel approach to enhance predictions for N, S, and V.

In previous studies, various methods and approaches based on intelligent models have been employed to classify N, S, and V classes, yet the classification results remain inadequate for clinical applications. Therefore, in this research, we aim to investigate the efficacy of a deep feature extraction method using WST, complemented by a second stage feature extraction through 1D CNN. Our objective is to improve prediction and classification results for the three classes.

The rationale for selecting the WST lies in its robust capability to extract both time-domain and frequency-domain features crucial for effectively distinguishing between the three classes. Furthermore, the choice of the 1D CNN in this study is justified by its inherent feature extraction stage, which facilitates the extraction of deeper features. Additionally, the 1D CNN has demonstrated remarkable performance in various classification tasks, underscoring its widespread applicability and effectiveness in classification endeavors.

The combination of these two techniques aims to address the limitations encountered in previous works and improve the prediction accuracy of the 3 ECG classes. This enhancement holds significant promise for advancing the field of automated detection of ARR in ECG. By integrating the WST and 1D CNN, our study seeks to surpass the constraints of prior methodologies and achieve more precise classification results.

III. Materials and Methods

A. Database Description

The research relies on publicly available data from PhysioNet, accessible at the following link: https://www.physionet.org/content/mitdb/1.0.0/. The ECG readings were extracted from the MIT-BIH Arrhythmia database, comprising 48 half-hour excerpts of two channel ambulatory ECG recordings [27].

The recordings were digitized at a rate of 360 samples per second per channel, with an 11-bit resolution over a 10 mV range. The records used in this study are taken from the lead II, because lead II is positioned along the axis of the heart, making it particularly sensitive to changes in heart's rhythm that occur in this plane. So, it’s an important tool for detecting ARRs.

In this study, recordings with paced beats were excluded from the MIT-BIH dataset, specifically four recordings (102, 104, 107, and 217) out of the total 48. The reason for excluding those patients from the analysis was that they had cardiac pacemakers, which had the potential to cause interference.

B. Data Preprocessing

Our study focuses on long-term ECG signals from the MIT-BIH database, aiming to classify heartbeats into three categories: N, S, and V. To achieve this, a QRS detection algorithm is essential for extracting distinct ECG heartbeats from a single recording. Numerous approaches have been explored in the realm of QRS detection, ranging from the foundational Pan-Tompkins algorithm [28] to wavelet-based techniques [29-30], and even machine learning models [31].

In our investigation, the Pan-Tompkins algorithm was opted due to its proven accuracy in QRS detection, achieving an impressive 99.3% accuracy when tested on the MIT-BIH arrhythmia database. Additionally, the algorithm exhibits a lower computational cost compared to alternative QRS detection models. This choice aligns with our goal of efficiently and accurately discerning QRS complexes in ECG signals for subsequent heartbeat classification.

Following the QRS complex detection using the Pan-Tompkins algorithm, 70 samples before and 70 samples after each R peak were extracted, resulting in a total of 141 samples per heartbeat. Fig. 1, Fig. 2, and Fig. 3 depict three distinct types of ECG heartbeats: N, S, and V. To accommodate variations in heart rate, the difference between the post-RR interval and pre-RR interval was incorporated into the samples.

To ensure a fair comparison with previous automated heartbeat classification models, a data split strategy consistent with state-of-the-art approaches was adopted. Similar to these studies, 44 MIT-BIH recordings (excluding four with paced beats) were partitioned into two subsets. Half of the recordings (DS1) were utilized for training, while the remaining constituted the test set (DS2). The distribution of the data used in this paper is outlined in Table II. This inter-patient data split methodology enhances the development of well-generalized model, capable of effectively classifying ECG from new, unseen patients.

In this paper, the DS1 subset was employed for model training and DS2 for testing. A notable observation within DS1 revealed a substantial class imbalance, where the N class boasted 46,596 instances, while the minority classes, S and V, were represented by 1,669 and 3,799 instances, respectively. Recognizing that training on such an imbalanced dataset could skew results towards the majority class and amplify bias, we implemented the Synthetic Minority Over Sampling Technique (SMOTE) [32]. SMOTE proved instrumental in mitigating this imbalance by generating synthetic instances for the minority class. This strategic approach aimed to rectify the skewed class distribution, and foster more equitable representation of each heartbeat type during training. By addressing this imbalance, we sought to enhance the classification performance of our model, ensuring its effectiveness across all classes.

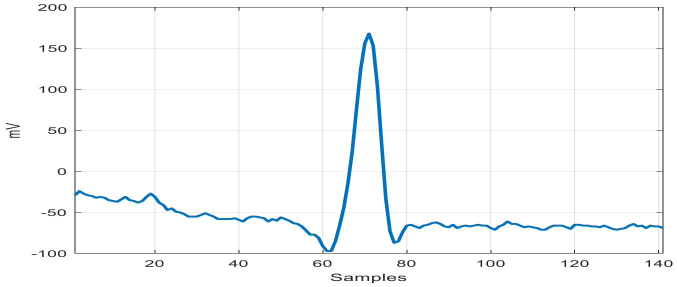

Fig. 1. Non-Ectopic beat.

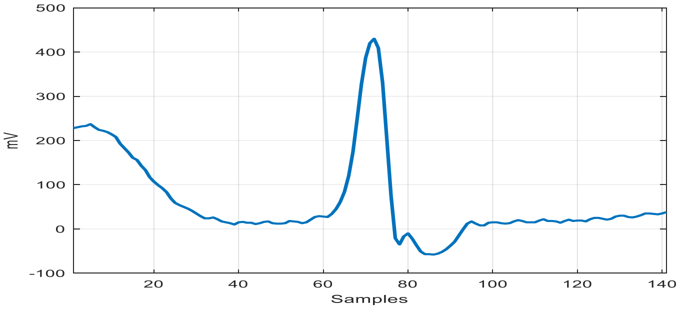

Fig. 2. Supraventricular ectopic beat.

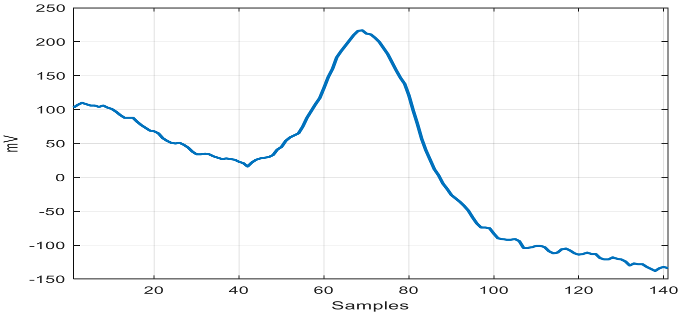

Fig. 3. Ventricular ectopic beat.

TABLE II. RECORDS AND HEARTBEAT CLASSES PARTITION

Partition	Patients ID	N	S	V
DS1	101, 106, 108, 109, 112, 114, 115, 116, 118, 119,122,124, 201, 203, 205, 207, 208,209, 215,220, 223, 230	46596	1669	3799
DS2	100,103,105, 111, 113,117, 121, 123, 200, 202,210, 212, 213,214, 214,219,221,222,228,231,232, 233,234	43478	1110	3681
Total		90074	2779	7480

C. Deep Features Extraction

To achieve accurate ECG heartbeat classification, it is crucial to employ a feature extraction technique. Two main types of features play a key role in this process: time-domain features, which capture and analyze signal amplitudes over time, and frequency-domain features, providing insights into different signal frequencies. However, traditional approaches like Fourier transform, commonly used for extracting frequency-domain features, lack temporal information, only revealing the frequencies present in the signal. Addressing this limitation, the wavelet scattering transform (WST) emerges as a solution. Fig. 4 illustrates the composition of a wavelet scattering network, featuring multiple layers where WST, akin to a CNN with cascading wavelets, is performed at each layer.

The WST offers features that exhibit stability against deformation, as well as invariance to translation and rotation. Notably, it serves as a potent technique for signal denoising and dimensionality reduction. Applied extensively in audio, image, and 1D signal analysis [33].

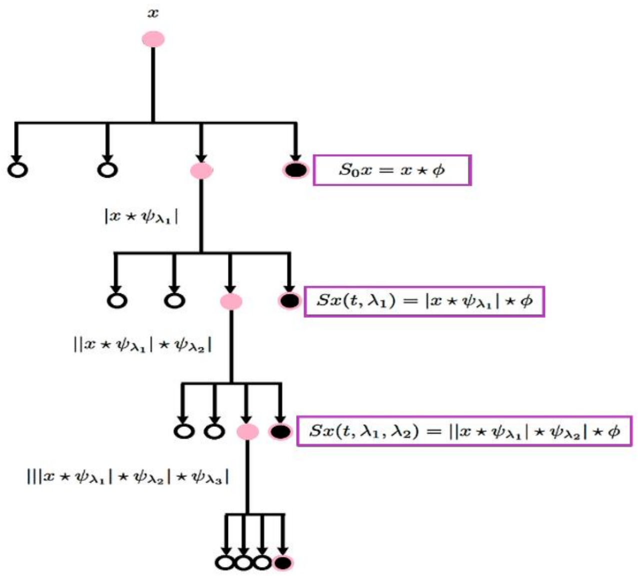
x
$S_0x = x \star \phi$
$|x \star \psi_{\lambda_1}|$
$Sx(t, \lambda_1) = |x \star \psi_{\lambda_1}| \star \phi$
$||x \star \psi_{\lambda_1}| \star \psi_{\lambda_2}|$
$Sx(t, \lambda_1, \lambda_2) = ||x \star \psi_{\lambda_1}| \star \psi_{\lambda_2}| \star \phi$
$|||x \star \psi_{\lambda_1}| \star \psi_{\lambda_2}| \star \psi_{\lambda_3}|$

Fig. 4. Scattering network architecture

This paper introduces the Morlet analytic wavelet, offering several advantages. Firstly, being a complex wavelet, it allows the utilization of both its real and imaginary components in convolution processes. Additionally, the wavelet features a low-pass filter represented by the modulus of this wavelet, facilitating down-sampling during the scattering transform.

Moreover, Fig. 5 highlights the remarkable similarity between the shape of this complex wavelet and the QRS complex in ECG heartbeats. This similarity enhances its sensitivity in analyzing and detecting ARR within ECG signals. The expression below represents the mathematical representation of the complex wavelet employed.

$$\psi(t) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-t^2}{2\sigma^2}} e^{i\omega t} \tag{1}$$

In the given expression, t corresponds to time, and σ stands for the standard deviation of the Gaussian function. ω is defined as 2πf, where f is the center frequency of ψ, and i is the imaginary unit. The envelope of the complex wavelet is characterized as a low-pass filter denoted as Φ in Eq. (2).

$$\Phi(t) = |\psi(t)| \tag{2}$$

The WST initiates by convolving x(t), which represents the signal being analyzed, with Φ.

$$S_0x(t) = x(t) * \Phi \tag{3}$$

The wavelet function ψ and the low-pass filter Φ are specifically designed to span the entire frequency range of the signal x(t). The low-pass filter introduces a form of averaging, ensuring locally invariant translation features of x. However, the initial order of the Wavelet Scattering Network (WSN) results in the loss of high frequencies, which can be restored by progressing to the subsequent order of the WSN.

In the 1st order of the WSN, an additional convolution was applied using the wavelet ψ_{λ_1} with the scale λ_1. Here, $\psi_{\lambda_1} \in \{\psi_{\lambda k}\}_{\lambda_k \in \Delta_k}$, where, $\psi_{\lambda k}$ represents the multi-scale high-pass filter bank, and Δ_k represents the family of wavelet indices with an octave frequency resolution Q_k.

$$|W_1|x = \{S_0x(t), |x * \psi_{\lambda_1}|\}_{\lambda_1 \in \Delta_1} \tag{4}$$

The 1st order scattering coefficients result from the convolution with the low-pass filter Φ.

$$S_1x(t) = \{|x * \psi_{\lambda_1}| * \Phi\}_{\lambda_1 \in \Delta_1} \tag{5}$$

To retrieve the information (high frequencies) lost during the application of the low-pass filter, the second order of the WSN was proceed.

$$|W_2|x = \{S_1x(t), |x * \psi_{\lambda_1}| * \psi_{\lambda_2}\}_{\lambda_2 \in \Delta_2} \tag{6}$$

Obtaining the 2nd order coefficients of the WSN involves applying convolution with the low-pass filter Φ.

$$S_2x(t) = \{||x * \psi_{\lambda_1}| * \psi_{\lambda_2}| * \Phi\}_{\lambda_2 \in \Delta_2} \tag{7}$$

Similarly, we iterate through this process to determine the coefficients of the nth order in the scattering network.

$$S_nx(t) = \{|..||x * \psi_{\lambda_1}| * \psi_{\lambda_2}| *..\psi_{\lambda_n}| * \Phi\}_{\{\lambda_1..\lambda_n\} \in \{\Delta_1..\Delta_n\}}$$ (8).

The final scattering matrix coefficients represented as:

$$Sx(t) = \{S_0, S_1, \dots, S_n\} \tag{9}$$

In this study, only a 2nd order WSN was used. This is because 99% of the energy of the signal under analysis is preserved in this layer. Furthermore, the addition of more layers to the network would result in a loss of information about the signal and an increase in computational cost.

For the representation of a single ECG heartbeat, applying the WST yields a tensor of size 34x5, which serves as the feature matrix. The scattering coefficients undergo critical down sampling based on the bandwidth of the low-pass filters, generating five-time windows for each of the 34 scattering paths. Each row and column in the tensor correspond to a specific scattering path and time window. Furthermore, the difference between post-RR and pre-RR interval was introduced through feature fusion, oversampling this value by a factor of 34. So, the final representation of the feature matrix is size 34x6. With a total of 48,269 testing instances, this results in a tensor size of 48,269x34x6. Same process is applied to training instances.

Utilizing the WSN with an invariance scale of 0.3 seconds and employing Q_1=8 and Q_2=1 as the quality factors for the 2 filter banks. The frequency bands of the 1st and 2nd filter banks are illustrated in Fig. 6.

Fig. 7 displays the scattering coefficients obtained through the application of WST. These coefficients serve as a visual representation of the hierarchical feature extraction process. The scattering coefficients indicate the presence and distribution of significant features within the signal, offering insights into the signal's composition at various levels.

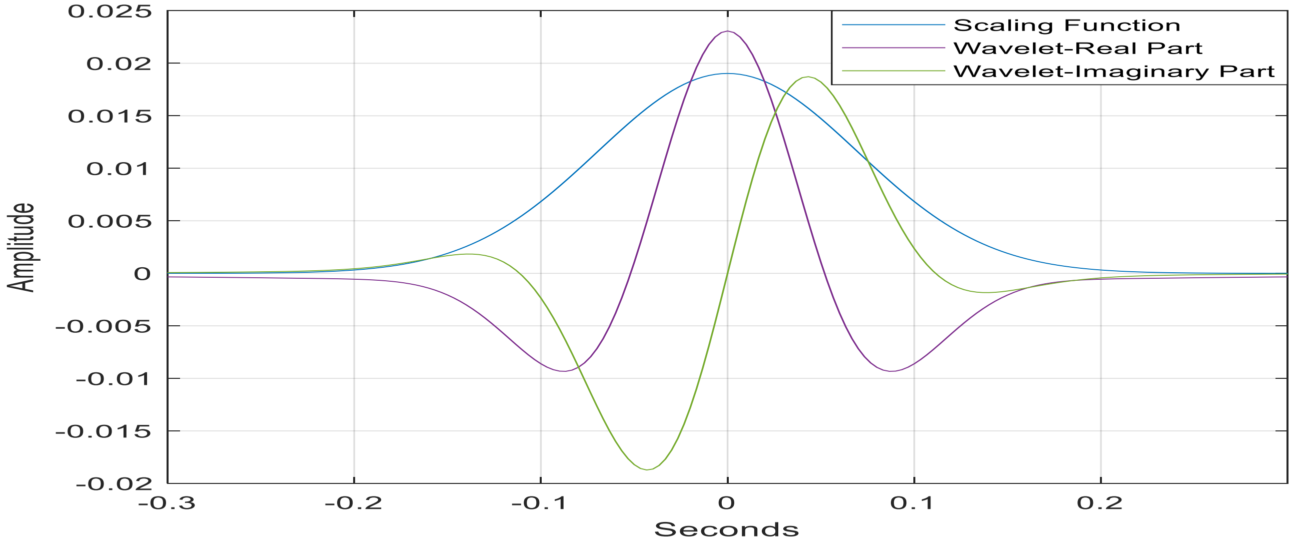

Fig. 5. Morlet Analytics wavelets.

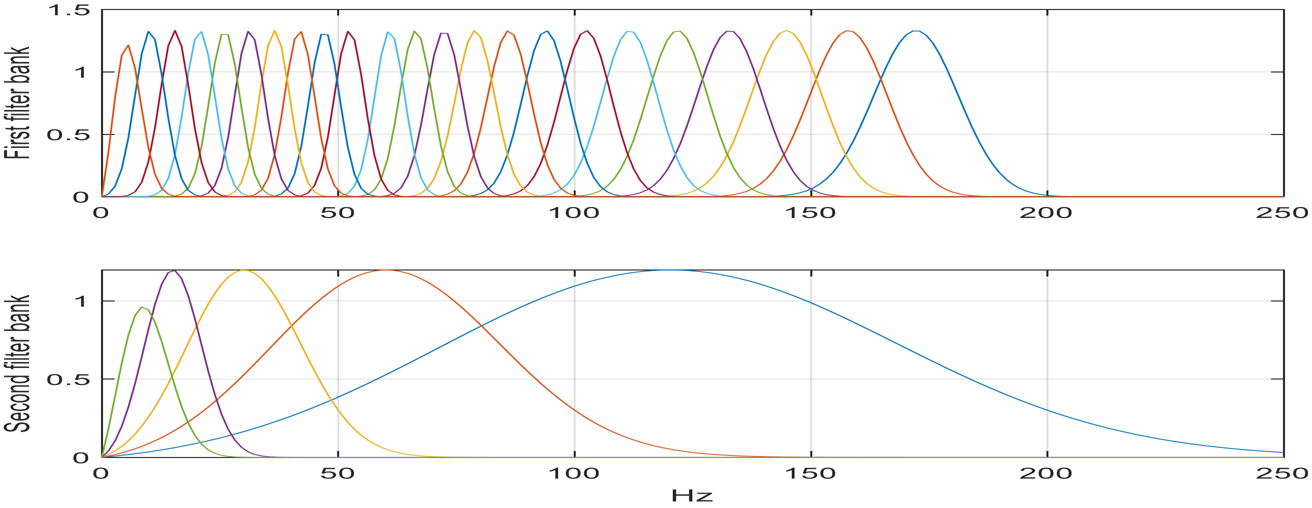

Fig. 6. Frequency bands of first and second filter banks.

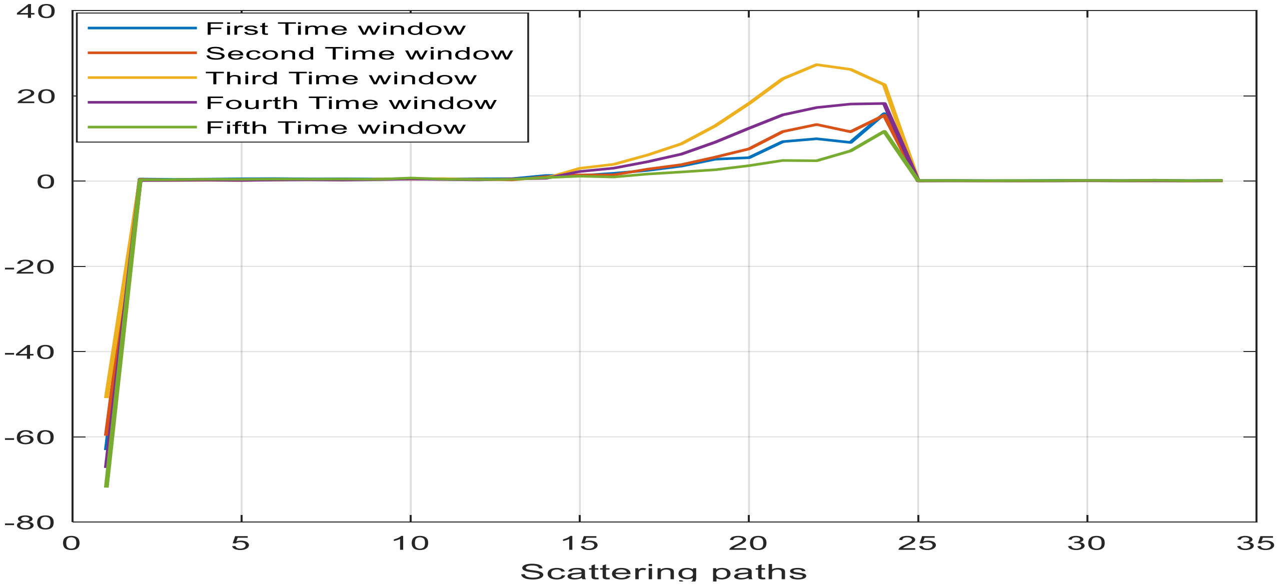

Fig. 7. Scattering coeffecients for one ECG heartbeat.

At a glance, one can observe the dominant patterns and structures captured by the different orders of scattering. Higher order coefficients reveal more intricate details and relationships within the signal, while lower order coefficients highlight foundational features, analyzing the spatial distribution and patterns in these coefficients aids in interpreting the discriminative aspects and inherent characteristics of the signal under consideration. This visual representation enhances the understanding of how the WST effectively captures and organizes relevant information for further analysis.

The WSN was implemented in the MATLAB environment, with the WSN parameters configured for an invariance scale of 0.3 seconds. The sampling frequency was set at 360 Hz.

D. Classification Model

In our research endeavor, a 1D Convolutional Neural Network (1D CNN) was meticulously utilized to address the intricate task of classifying ECG heartbeats into three discernible categories. This deliberate choice of utilizing a 1D CNN stems from its widely acknowledged effectiveness in both the realms of classification and feature extraction, a critical aspect of signal analysis.

The architecture of the 1D CNN unfolds in a systematic manner, featuring two fundamental components. In the initial phase, convolution is employed with fixed-size filters to extract salient features from the signal under scrutiny. This process plays a pivotal role in enhancing the network's ability to discern subtle patterns inherent in ECG data. The subsequent infusion of non-linearity is achieved through the application of the (ReLU) activation function, a prevalent choice in this context due to its efficacy in preventing vanishing gradient.

Moving forward, the convolutional stage is followed by pooling, strategically implemented to reduce the dimensionality of the extracted features. This reduction not only aids in computational efficiency but also enhances the network's ability to focus on the most relevant information for subsequent classification steps.

The final stages of the 1D CNN involve a fully connected layer, which serves as a critical bridge between the extracted features and the subsequent classification process. The output layer, equipped with an activation function tailored for signal classification, culminates in the conclusive step of categorizing ECG signals into their respective classes.

One notable distinction in our approach is the deliberate choice of a 1D CNN over a 2D CNN. This decision is rooted in a keen consideration of computational costs, with the 1D CNN proving to be a more resource-efficient solution. This pragmatic approach underscores our commitment to not only achieving high classification accuracy but also optimizing the computational demands, making our methodology a judicious choice for real-world applications.

Our designed 1D CNN boasts a sophisticated architecture comprising a total of 11 layers. The inaugural layer, known as the sequence input layer, plays a crucial role in organizing input rows as sequences, setting the stage for subsequent treatment. Following this, our 2nd layer takes the form of a convolution layer with a filter size of 3 and 64 filters. Notably, a fixed padding size of [2,0] was employed to enhance the convolutional process. In the 3rd layer, the non-linearity was infused into the model through the ReLU activation function. Finally, the 4th layer introduces a normalization step, a pivotal measure prevented the exploding gradient phenomenon. In the 5th layer, another convolution layer was employed with a filter size of 3 and an increased 128 filters. Accompanied by a padding size of [2,0], this convolutional stage is complemented by ReLU activation and normalization.

The convolution, ReLU, and normalization processes are represented by the following Eq. (10), Eq. (11) and Eq. (12).

$$y_i = b + \sum_{j=0}^{n-1} W_j \, X_{i+j} \tag{10}$$

In the output feature map, y_i represents the output at position i where b is the bias term, w_j is the weight at position j in the filter kernel, x_{i+j} refers to the input at position i+j in the input feature map, and n denotes the width of the filter kernel. The ReLU function sets negatives to zero, leaving positives unaffected.

$$y_i = \max(0, x_i) \tag{11}$$

The normalization process can be modeled as follows.

$$Z = \frac{x - \mu}{\sigma} \tag{12}$$

where, μ designed the mean value and **σ** is the standard deviation.

In the 8th layer, global average 1D pooling is applied to decrease dimensionality. Subsequently, a fully connected layer with an output layer featuring a SoftMax activation function follows. Eq. (13) and Eq. (14) below illustrate the fully connected layer and the SoftMax activation function.

$$Z_j = \sum_{i=1}^{n} W_{ij} \, X_i + \, b_j \tag{13}$$

$$Y_c = \frac{e^{Z_c}}{\sum_{k=1}^{3} e^{Z_K}} \tag{14}$$

where, Y_c is the predicted probability for class c after applying the SoftMax activation function.

Fig. 8 illustrates the architecture of our 1D CNN designed for the classification process, while Table III displays the specific parameters set for training the model.

E. Evaluation Metrics

In assessing the efficacy of our model and conducting a comprehensive comparison with state-of-art models, it becomes imperative to employ a spectrum of performance metrics. Key measures, including accuracy, sensitivity, specificity, precision, and the F1 score, play pivotal roles in providing a nuanced evaluation of the model's capabilities.

$$\text{Accuracy (ACC)} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{15}$$

$$\text{Precision (PPV)} = \frac{\text{TP}}{\text{TP+FP}} \tag{16}$$

$$\text{Recall or Sensitivity (SEN)} = \frac{\text{TP}}{\text{TP+FN}} \tag{17}$$

$$\text{Specificity (SPE)} = \frac{\text{TN}}{\text{TN+FP}} \tag{18}$$

$$\text{F1 score (F1)} = \frac{2*\text{precision}*\text{sensitivity}}{\text{precision}+\text{sensitivity}} \qquad (19)$$

F. System Description

All algorithms were implemented using MATLAB version R-2021b on a Windows server. The system used for execution had an Intel Core i5 6300U processor running at 2.40 GHz, equipped with 12 GB of RAM, and operated on a 64-bit.

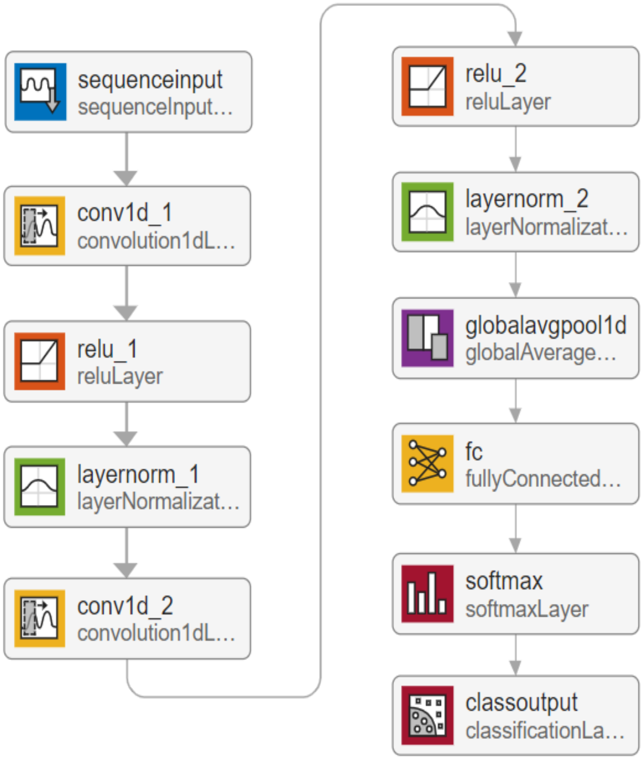

Fig. 8. 1D CNN architecture.

TABLE III. 1D CNN HYPERPARAMETERS

Hyperparameters	Values
Optimizer	adam
No. epochs	300
Learning rate	0.01
Batch size	64
Weights initializer	glorot
Bias inintializer	zeros
No. layers	11
Input size	34*6
Input size of fully connected layer	128
Output size of fully connected layer	3
No. Classes	3
Validation frequency	500

IV. RESULTS AND DISCUSSION

A. Results

This paper introduces an innovative method for classifying ECG heartbeats into three categories (N, S, and V) following the AAMI standard. The primary goal is to improve accuracy, sensitivity, specificity, and F1 score for each class.

To ensure a fair comparison with existing models, the data was divided into two subsets: DS1 for training and DS2 for validation, aligning with the MIT-BIH arrhythmia database.

Our approach begins by employing the Pan-Tompkins algorithm for QRS detection, enabling the calculation of differences between post-RR intervals and pre-RR intervals.

Subsequently, the WST was utilized to extract morphological features from ECG heartbeats. Combining these features with the calculated post-RR and pre-RR results in a 34x6 matrix for each ECG heartbeat. This matrix is then fed into a specially designed 1D CNN for classification, as illustrated in Fig. 9.

By integrating these techniques, the classification performance aimed to be enhanced and contributed to the field of ECG heartbeat analysis.

After training our 1D CNN model with DS1 heartbeats, it was tested on DS2, revealed notable results. Among 43,478 actual N heartbeats, the model correctly identified 42,891, but intriguingly, it misclassified 191 N heartbeats as V and 396 as S. This misclassification stems from the morphological closeness between N and S classes. Similar challenges were observed in the S class, where out of 1,110 actual S heartbeats, 863 were accurately detected, but 232 were misclassified as N and 15 as V.

Conversely, for the V class heartbeats, out of 3,681 actual V heartbeats, the model successfully classified 3,580, with only 91 misclassified as N and 10 as S. This outcome aligns with the distinct morphological differences observed between V and S.

The precision analysis unveils that the model excels in detecting N and V classes but demonstrates lower precision for S heartbeats. This nuanced understanding is crucial, emphasizing the challenges posed by morphological similarities, especially between N and S classes.

The testing data's confusion matrix, depicted in Fig. 10, encapsulates these findings, providing a visual representation of the model's performance across the three heartbeat categories.

Our model's performance was evaluated using various metrics. Based on the confusion matrix in Fig. 10, our model achieved an average accuracy of 98.71% across three classes. The average precision stood at 87.27%, with an average sensitivity of 91.22%. Additionally, an average specificity of 97.31% and an average F1 score of 89.13% was attained.

B. Discussion

In this research, a comparison with state-of-art models was conducted, utilizing the MIT-BIH arrhythmia database and adopting the same inter-patient data partitioning (DS1 for training and DS2 for testing). The results, illustrated in Table IV, underscore the superior performance of our proposed model across various evaluation metrics.

Notably, for the N class, our model demonstrated remarkable precision at 99.25%, coupled with a specificity of 93.26% and F1 score of 98.95%. Furthermore, our model showcased superiority in the S class, achieving a noteworthy sensitivity of 77.75%. This trend persisted in the V class, where our model outperformed the state-of-art models across multiple metrics, attaining a sensitivity of 97.26%, specificity of 99.54%, and an F1 score of 95.89%. These results underscore the efficacy of our model in effectively distinguishing between N, S, and V.

TABLE IV. COMPARISON WITH STATE OF ART MODELS

Methods	**N**				**S**				**V**			
	SEN	***PRE***	***SPE***	***F1***	***SEN***	***PRE***	***SPE***	***F1***	***SEN***	***PRE***	***SPE***	***F1***
Sellami et al. [18]	94	98	82.55	95.95	61.96	52.96	97.89	57.10	87.34	59.44	95.91	70.73
Li et al. [19]	88.52	98.80	91.3	93.37	82.04	30.44	92.8	44.40	92.05	72.13	97.54	80.88
Garcia et al. [20]	94.54	93.33	80.8	93.93	35.22	65.88	98.83	45.90	88.35	79.86	94.92	83.89
Wang et al. [21]	**99.04**	98.64	87.95	98.83	70.75	**77.0**	**99.51**	**73.74**	94.35	**95.32**	99.54	94.83
Takalo et al. [22]	91.89	97	76.93	94.37	62.49	55.86	98.11	58.98	89.23	50.58	94.02	64.56
Junaid et al. [23]	98.48	97.39	76.82	97.93	44.01	64.50	99.01	52.32	92.96	89.62	99.22	91.25
Present Work	98.65	**99.25**	**93.26**	**98.95**	**77.75**	68.01	99.14	72.55	**97.26**	94.56	**99.54**	**95.89**

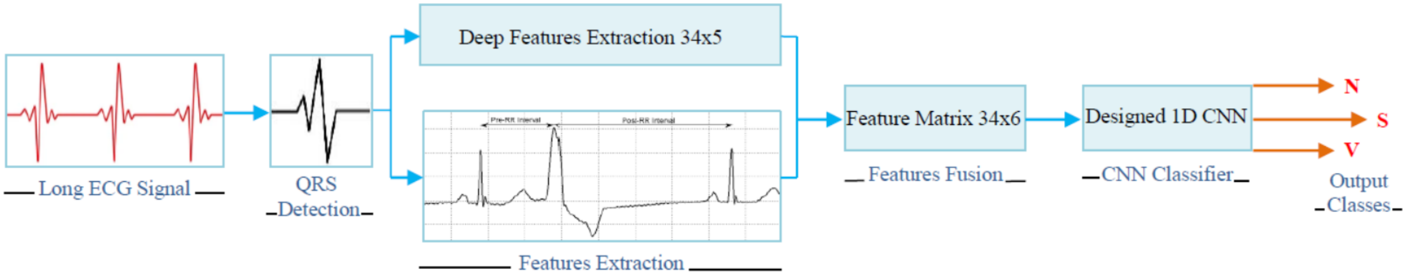

Fig. 9. An overview of the sequential steps for classifying heartbeats

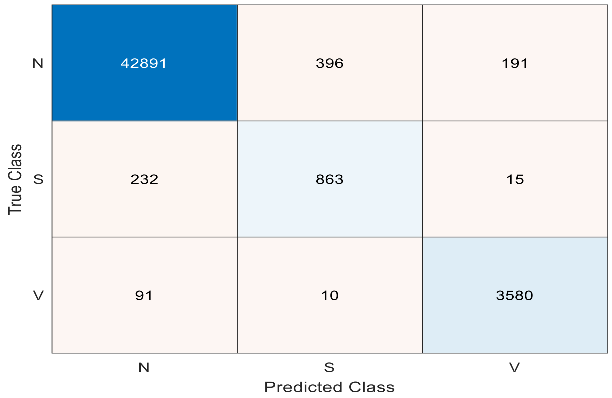

Fig. 10. Testing confusion matrix.

In our investigation, our analysis was extended by comparing the overall accuracy achieved in this study with results from previous works, as detailed in Table V. Sellami et al. [18] achieved an overall accuracy of 92.4% in identifying ECG heartbeats with their proposed approach. In contrast, Li et al. [19] attained an overall accuracy of 88.34% with their method. Among all the other previous works, Wang et al. [21] achieved the highest overall accuracy of 97.68%. The findings reveal that our proposed model successfully detected 47,334 out of 48,269 instances during testing, yielding an impressive overall accuracy of 98.06%. This value signifies that our model accurately classified 98.06% of the tested heartbeats. Importantly, this overall accuracy underlines the superiority of our model over existing automated classification models.

TABLE V. OVERALL ACCURACY COMPARISON WITH OTHER PREVIOUS WORKS.

Methods	**Overall accuracy %**
Sellami et al. [18]	92.4
Li et al. [19]	88.34
Garcia et al. [20]	88.99
Wang et al. [21]	97.68
Takalo et al. [22]	89.91
Junaid et al. [23]	95.99
Present Work	**98.06**

V. Conclusion

In this study, an approach was introduced by combining WST for deep feature extraction with 1D CNN classifier. Our model's evaluation, employing inter-patient partitioning, enhances its generalizability for potential clinical applications.

Our results showcase the superiority of our model over state-of-art models. Achieving an overall accuracy of 98.06%, our model excelled in distinguishing between three heartbeat classes. Specifically, it demonstrated a sensitivity of 98.65%, precision of 99.25%, and specificity of 93.26% for the N class. For the S class, our model achieved a sensitivity of 77.75%. Additionally, it outperformed in the V class with a sensitivity of 97.26%, precision of 94.56%, specificity of 99.54%, and an F1 score of 95.89%. These results highlight the significant advancement our model brings to the field.

VI. Limitations and Future work

Despite these successes, our method has limitations. The computational cost of our feature extraction method is notable due to numerous arithmetic operations during convolution. Furthermore, our model shows room for improvement in evaluating the S class, with an F1 score not exceeding 72.55%.

Future work will concentrate on mitigating computational costs by identifying essential wavelets for optimal results. Additionally, we aim to conduct an in-depth analysis of ECG heartbeats to enhance our model's predictive capabilities for the S class. These advancements will further solidify the applicability and efficiency of our proposed method.

Data Availability

ECG readings were taken from: https://www.physionet.org /content/mitdb/1.0.0/

Conflict of interest

We confirm that all authors declare no conflicts of interest.

Acknowledgment

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Leveraging Machine Learning for Enhanced Cyber Attack Detection and Defence in Big Data Management and Process Mining

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Abstract—**The rapidly developing field of "Commercial Operation Divergence Analysis," this research seeks to identify and understand differences in commercial systems that exceed expected results. Approaches in this domain aim to identify the characteristics of process implementations that are associated with changes in process effectiveness. This entails identifying the features of procedural behaviours that result in unpleasant results and figuring out which behaviours have the biggest impact on increased efficiency. As the scale and complexity of big data management and process mining continue to expand, the threat of cyber-attacks poses a critical challenge. This research leverages machine learning techniques for the detection and defence against cyber threats within the realm of big data management and process mining. The study introduces novel metrics such as Skewness, Coefficient of Variation, Standard Deviation, Maximum, Minimum, and Mean for assessing the security state, utilizing variables like SPI, SPEI, and SSI. The research addresses prior issues in cyber-attack detection by integrating machine learning into the specific context of big data and process mining. The novelty lies in the application of Skewness and other statistical metrics to enhance the precision of threat detection. The results demonstrate the effectiveness of the proposed methodology, showcasing promising outcomes in identifying and mitigating cyber threats in the given dataset and which makes use of Support Vector Regression (SVR), has a standard deviation of 0.9, which is consistent with the variability shown in SVM. The results demonstrate a significant achievement, with a Mean Absolute Error (MAE) of 0.98, indicating the efficacy of the proposed approach in providing accurate and timely insights for cyberattack detection and defense, thereby enhancing the overall security posture in data-intensive systems. The results highlight how well the proposed method extracts significant insights from complicated event data, with important ramifications for real-world application and decision-making procedures.**

Keywords—Machine learning; data mining; cyber-attack detection; big data; support vector regression

I. Introduction

Effective extraction operations depend on the deep mine's ability to maintain a healthy and secure air atmosphere [1]. A crucial step in the analysis of data is outlier detection. Hawkins states that atypical is "a thing whether diverges sufficiently form other items as to be assumed that it has been produced by an alternate method" [2]. In 2008, the Global Financial Crisis (GFC) and the demise of the coal mining "super cycle" put a stop to a period of production-focused tactics during which operational costs increased faster than output [3]. Because it presents especially challenging compromises the extractive and material extraction sector is a desirable test case for the study of contamination. Individual plants may provide enormous value, up to millions of dollars annually [4]. Studies had lately claimed that the application of Process Mining (PM) might address these drawbacks through enabling auditors to efficiently and primarily automatically analyse all of the databases employing historic and/or present-day information [5]. Nevertheless, a number of issues brought on by the extraction and use of coal assets, including as sinkholes, erosion of soil, landslides, and the demolition of buildings, have had a significant detrimental impact on the daily lives and assets of local populations [6].

Mining processes is a field of study who tries to enhance process enhancements by offering based on reality observations on previous procedure implementations. The topic sits among system modelling and evaluation and intelligence computing as well as data mine on one's hand. Process variation assessment is described as a collection of methods that allow to contrast more than one event records belonging to various company procedure versions for the purpose to identify the differences between them [7]. A prime instance of contaminated soil includes the soils that make up anthracite mine dumps. The sedimentary layers that cover a coal seam are where the initial soil was formed. The excess soil is typically excavated using various excavators, then delivered into the spoil site via lorries or belt conveyors and deposited form different heights, either with or no choosing the material [8].

Multiple research studies indicate that these last class of computations, machine learning algorithms (MLAs), can be more accurate than statistical methods like discriminant evaluation or logistic regression, particularly if the feature space to be studied is complicated (i.e., once the dimension of the input feature time is believed to be quite large and the connection between the intended contributions along with the feedback transparent include is predicted to be non-linear) and the data sets being used are anticipated to include distinct characteristics [9]. One the contrary, machine learning is a branch of computing which seeks to give machines or different gadgets the capacity to understand sans needing directly controlled. It tries to provide methods and mathematical models for data-driven learning and forecasting. Upon accomplishment, machine learning techniques are used to simulate characteristics of the input in relation to anticipated result, predict production attributes in relation to past information, and characterise the behaviour within the data. A possible approach to predicting wind power using velocity data is machine learning techniques [10]. Machine learning has been immensely successful as information quantities and types have increased because of its ability to examine complex trends in seen information and generate predictive models or choices on fresh data. In the literature, a variety of machine learning methods and algorithms have been published [11].

Predicting how a business operation will behave in the years to come is an essential corporate competence. Procedure prediction, a form of statistical analysis used in management of business processes, uses information from previous process occurrences to forecast future ones [12]. Customer service representatives adjusting to requests about the amount of time left until an issue has been settled are a few examples of use instances. Other use cases include production managers forecasting the length of a manufacturing procedure for improved scheduling and higher utilisation or case supervisors determining probably violations of regulations to reduce business risk [13]. One kind of procedure mining work, called procedure learning, looks for a model that describes the behaviour of an organization's process using information about how it has previously been executed. The log of events is mapped onto a procedure model using a method known as a process identification procedure, which guarantees the model in question is a good representation of the behaviour shown in the event log [14].

Our approach prioritizes adaptability to external influences by employing dynamic updating mechanisms. We continuously monitor cyber security policies, track advancements in attack techniques, and stay abreast of technological shifts. This proactive approach allows us to incorporate new knowledge into our models promptly, ensuring their relevance and effectiveness in evolving cyber security landscapes. Additionally, we leverage techniques such as transfer learning and ensemble methods to enhance model robustness and resilience to changing external factors. The proposed model exhibits robustness to changes in feature selection and extraction methods through rigorous validation and sensitivity analysis, ensuring consistent performance across varying feature sets. Additionally, automating feature engineering enhances efficiency and scalability while reducing the risk of human error, bolstering the reliability and adaptability of our models. Regular audits and oversight mechanisms further reinforce data privacy measures, mitigating potential privacy concerns and promoting responsible data stewardship in cyber security practices. Implementing the methodology may face challenges such as organizational resistance to change, integration with existing infrastructure, and compliance with regulations.

The following are the research Primary Contribution:

- The application of machine learning algorithms allows for improved accuracy and predictive power in identifying the characteristics of process behaviour that contribute to efficiency shifts.
- Machine learning algorithms provide a means to uncover the relevant factors that significantly affect process efficiency. By analysing the event logs and applying the proposed Declare-based coding, the research identifies the most influential aspects of a procedure, allowing organizations to focus on these factors for process optimization.
- The combination of machine learning algorithms and the proposed encoding technique constitutes an effective tool for the analysis of processes.
- The research compares the performance of different machine learning algorithms, such as Standardized Stream flow Index, Gene Expression Programming, Support Vector Regression, and M5 Model Tree. This comparative evaluation helps in understanding the strengths and weaknesses of each algorithm and provides guidance on selecting the most suitable approach for a given context.

Section I, the introduction, provides an overview of the research topic, establishing its relevance and context. Section II, related work, explores existing literature and research in the field to highlight gaps or connections with the current study. Section III, the problem statement, clearly defines the specific issue or gap that the research aims to address. Section IV, methodology, outlines the approach and techniques employed to conduct the study. Section V presents the results and engages in a discussion, while Section VI concludes the research, summarizing key findings and suggesting potential avenues for future exploration.

II. RELATED WORKS

Richetti et al. [15] proposed to determine the aspects of a procedure which most affect its efficiency, they first use Treatment Learning as an original method in the realm of Deviation Mining. This is a novel encoding method enabling vector-based representations of process occurrences. The suggested encoding method may find more expressive solutions since it is built on declaring restriction framework fulfilment. Using publicly accessible logs of events from actual procedures, they do a number of tests that contrast our suggestion to the state-of-the-art activity decoding methods. The findings demonstrated that behavioural learning offered actionable and more descriptive insight from events logs when combined with our suggested Declare-based encoding, making it a useful tool for the analysis of processes.

Al-Shehari et al. [16] proposed the use of feature resizing and quick encoding strategies are used in the framework to alleviate the potential skew of identification outcomes that might emerge from an ineffective decoding procedure. The artificial minority sampling too much method (SMOTE) is additionally employed to alleviate the data set's balance problem. In order to discover a highly precise classification which can identify data leakage events carried out by malevolent outsiders throughout the crucial time when they depart an organisation, renowned machine learning methods are used. By applying our mathematical framework on the CMU-CERT Insider Threat Dataset and contrasting its results with the real world, we demonstrate the notion behind it. The results of the experiment demonstrate that our framework outperforms other methods which have been evaluated on the identical data in terms of detecting internal leakage of information events, with an AUC-ROC value of 0.99. The suggested framework offers practical approaches to deal with potential bias and class imbalance concerns in order to design a system that effectively detects insider data leaking.

Roldán et al. [17] proposed an approach that uses technologies like augmented reality and data mapping to teach workers in assembly operations. Firstly, skilled employees do assembly in accordance with their knowledge using a fully immersive environment. The next step is to use process mining methods to extract assemble model in the logs of events. Lastly, to understand the groups what the expert employees incorporated into the framework, learner employees utilise an improved immersion display with suggestions. Construction block experiments were designed as a toy example, and studies on a group of participants have been conducted. The outcomes demonstrate the suggested education system's competitiveness against more traditional options. It bases itself on procedure mining and mixed reality. In terms of mental effort, vision, learning, outcomes, and how they perform, user ratings are also superior.

Helm et al. [18] proposed 38 procedure mining instances related to health care reported from 2016 to 2018 that discussed the instruments, methods, and methodologies used as well as specifics on how the log data were found to have been medically significant. Utilising the common clinical coding schemes SNOMED CT and ICD-10, researchers then connected the diagnostic characteristics of the patient encounter setting, clinical speciality, and diagnosis of illness. The possible results of utilising a standardised method for categorising medical terms and events log data using common clinical codes are also highlighted.

Weinzierl et al. [19] proposed several prospective business process monitoring (PBPM) strategies that attempt to forecast potential process behaviours while the procedure is being executed. Methods for predicting subsequent event in particular have considerable promise for enhancing practical company processes. Many of these methods use deep neural networks (DNNs) and take into account data pertaining to the environment where the operation is occurring to provide recommendations that tend to be more reliable. Nevertheless, an in-depth analysis of such methods is lacking in the PBPM literature, making it difficult for academics and industry professionals to decide which approach is appropriate for a particular event log. To address this issue, they statistically assess the prediction performance among three potential DNN structures using five tried-and-true encoding methods and five context-rich real-world logs of events. They offer four conclusions that might aid researchers and practitioners in developing fresh PBPM methods for anticipating upcoming actions.

The literature review showcases several developments in machine learning and process mining applications across a range of industries. But there is a clear research vacuum when it comes to combining these technologies to improve cyber security—more especially, when it comes to insider threat defence and detection. Research on process mining, efficiency assessment, healthcare procedures, and prospective business process monitoring has been greatly aided by studies by Richetti et al. [15], Al-Shehari et al. [16], Roldán et al. [17], Helm et al. [18], and Weinzierl et al. [19]. However, none of these studies specifically address the crucial problem of using machine learning for cyber security in the context of Big Data Management and Process Mining. Novel encoding strategies, predictive modelling, or anomaly detection approaches specifically designed for cyber security in massively distributed data settings are not well explored in the literature. This gap in the literature highlights the necessity for a thorough investigation that carefully incorporates machine learning techniques into cyber security frameworks, with an emphasis on the particular difficulties presented by big data and process mining scenarios.

III. Problem Statement

The problem statement of this work is to address the limitations of existing techniques for business process deviance mining. These techniques are based on the extraction of patterns from event logs but have limited expressiveness, particularly in capturing complex relationships in highly flexible processes. The previous research is to apply Treatment Learning, a novel approach in the context of machine learning, to identify the characteristics of a process that have the most significant impact on its performance. The study aims to compare the proposed encoding technique with current process encoding techniques through a series of experiments using publicly available event logs from real-life processes [15]. By incorporating machine learning approaches to strengthen cyber-attack detection and defence mechanisms, particularly within the fields of Big Data Management and Process Mining, the research seeks to expand the breadth of cyber security while boosting the effectiveness and resilience of digital systems.

IV. Regarding Discovery and Declarative Process Modelling

Conventional urgent process diagrams are produced by the majority of mining process methods. These methods work effectively for organised processes since there aren't numerous additional ways an operation may be carried out. Declarative language modelling is suggested as a way to create an improved equilibrium amongst flexibility and guiding support for these types of models, despite the fact that many of these approaches are capable of handling event logs form flexible or unorganised models. Due to expressive modeling's relevance to log files from dynamic or unstructured processes, the potential of mining declarative models has also emerged. Potential bottlenecks may arise in resource-intensive tasks such as model training and feature extraction, requiring adequate computational resources and optimization strategies. To mitigate these challenges, we implement techniques such as data partitioning, caching, and resource allocation optimization to ensure efficient utilization of computational resources and maintain scalability as data volumes increase.

Declaring continues to be the most commonly employed languages for studies regarding declaratory modelling and mineral extraction, although having very little application in business. This is because it's versatile and particularly suited for use in extremely volatile procedures, which are characterised by extreme complexity and variety. The addition enables associations among actions taken upon KiPs to be described using domains limitations as opposed to sequential ordering. Additionally, it enables occurrences in a KiP to signal chronological ties, behavioural consistency restrictions, or choice-of-action relationships in its instances by using these extra notions. Compliance with laws and regulations controlling the application of machine learning for cyber security in various sectors and regions is given top priority in our approach. In addition, we keep clear records of all procedures, guaranteeing responsibility and traceability for our compliance initiatives. On the other hand, difficulties could emerge because regulations are dynamic and have different meanings in different places. The proposed models are designed to complement human-driven cyber security processes by providing automated support in threat detection and response. A collaborative approach where the proposed models serve as decision- support tools, aiding human analysts in identifying and prioritizing threats more efficiently. The models leverage time-series analysis methods to identify and respond to cyclical or recurring patterns in threat behaviour. Through this approach, the models demonstrate the ability to adapt to changes in threat behaviour over different time intervals, ensuring robust and effective threat detection capabilities in dynamic cyber security environments.

Deviance mining with machine learning and declare-based encoding of event logs in rapidly evolving environments like cyber security, where threats change constantly, machine learning models face challenges due to their assumption of stationary data distributions. This means they struggle to adapt to new patterns and trends. To overcome this, techniques like online learning algorithms and anomaly detection are crucial. Online learning allows models to update in real-time, while anomaly detection helps identify unusual behaviour. By employing these adaptive methods, machine learning models can better keep pace with evolving threats and enhance cyber security defenses. Machines are the simplest collection of rules that may be used in machine learning to discriminate between circumstances that include numerous highly weighted classes and scenarios with few strongly weighed categories. Machine learning, within contrast to association-rule mineral extraction, specifies a preferred type worth, that serves as a benchmark for weighing various class values and allows it to highlight machines with strong or poor performance as determined by a particular class characteristic in a dataset. Diverse datasets play a pivotal role in enhancing the generalizability of machine learning models. Models trained on diverse datasets are inherently more adaptable to variations across industries, company sizes, and geographic locations. This adaptability broadens the applicability of the models, ensuring they can effectively perform across a variety of contexts. By exposing the model to a wide range of scenarios and data distributions, diverse datasets enable the model to learn robust representations and patterns that transcend specific instances, thereby enhancing its ability to generalize and make accurate predictions in real-world scenario. Fig. 1 shows the steps to perform dataset encoding and machine learning analysis.

They introduce a unique rules-based technique to analyse company procedure footprints in the next section. By using a machine learner to find those intriguing regulations that have the greatest impact on the results of company procedure cases, our idea builds on previous methodologies centred around rule mining for associations and comparison items sets mine. Usually, indicators of success may be used to track system outputs. As a result, it can be seen trace-level indicators of success as trace-level characteristics that may be utilised as class variables in machine learning applications.

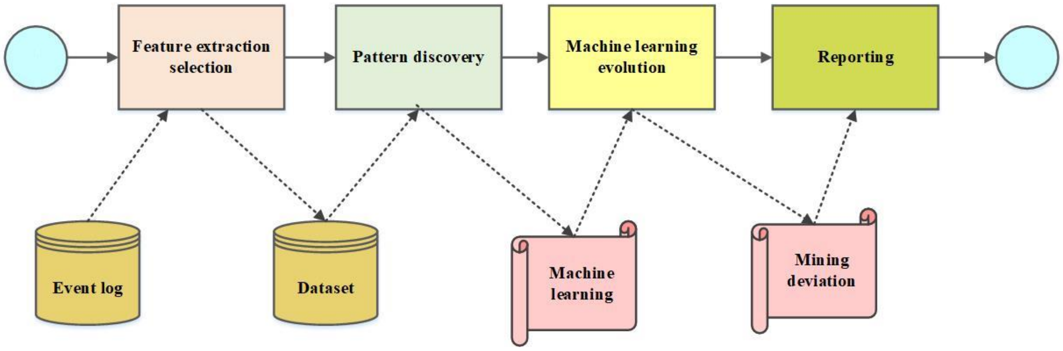

Fig. 1. Steps to perform dataset encoding and machine learning analysis.

It is crucial to bear in mind which (Process Efficiency Indicator) PPIs can be present at additional levels for abstractness in relation to business procedures, such as at the stage of activity, in which a particular task might be tracked from a PPI without consideration of the outcome of every other task carried throughout the same procedure. At the leadership threshold, it can be more important to keep track of a business' overall efficacy, which is often accomplished by combining the findings of a trace-level PPI. For instance, management is interested in monitoring a service level agreement that requires at least 95% of problems to be resolved within 24 hours, thus they would like to measure the amount of incidents resolved in less than 24 hours. This PPI identifies every procedure trail according to its finish time. It is an incorporation of a tracing-level PPI. Trace-level PPIs are of importance for the purposes of this work.

The idea behind machine learning is this, given a realisable choice, demonstrating the disparities among possibilities could prove more obvious than presenting every single event. As opposed to just listing the details of the present-day scenario, a machine learner quickly determines the critical aspects that most affect that circumstance.

A company's record of events might be transformed into a set of data for the purposes of machine learning. Following that, they describe a compression strategy that mines an archive of processes traces for features using declarative mining of processes. Declare's expressiveness is sufficient to record both basic count of each task and complex related to time interactions between pairs of activity. The idea is to use only one, condensed syntax in this manner to record both basic and complicated themes that could be present in an event log. As far that we comprehend, research has not yet investigated a declarative-language oriented encoding strategy to build vector illustrations of process occurrences.

TABLE I. SEQUENCE ENCODING

h_{id}	σ	boa			bigram		mrs		mra	
		x	*y*	*z*	*xy*	*xz*	*xy*	*xyz*	*x,y*	*X,y,z*
h_1	xyzxy	2	1	2	1	1	1	1	1	2
h_2	xyzx	2	1	1	0	1	0	0	1	2
h_3	xyzyzx	3	1	2	1	1	1	1	1	3

Table I is a non-exhaustive illustration of characteristics that may be retrieved given the occurrences of events inside the context of multiple activity traces that together make up a log of events P′. The illustration used known coding methods including bag-of-activities (boa), bigram, maximum repeat sequence (mrs), and maximal repeat alphabet (mra). Such encoding techniques track the frequency with which each encoding pattern is present in the process traces. The choice containing directly extracting tracing-level characteristics off the set h_{attr} of an operation trace and adding those into the collection of instance properties j_{attr} is also taken into account by our methodology. It is feasible to convert the incident log P′ to a datasets after extraction properties from a set of activity traces H ′ by transferring each h to H ′ to a dataset instance q, so that each q = $\left(h_{id}, h_{attr}, c_{name}\right)$, with $q_{1.....n} \in X^{'}$.

TABLE II. EVENT –LOG USING BOA ENCODING

h_{id}	x	y	z	et	Pc (c_{name})
h_1	2	1	2	4.50	false
h_2	2	1	1	3.20	true
h_3	3	1	2	7.30	false

The incident log change example's information is shown in the Table II. Imagine the identical examples traced from before that additionally have additional trace-level characteristics: processing duration (et), in days, as well as effective process conclusion (pc), containing an integer categorization value of "True, False." This provides an illustration of how an event log may be completely transformed into a dataset. A finite a number of occurrences within each trace $h_{1..3}$ may then be encoded using an encoding approach, such as bag-of-activities. Four unique qualities (characteristics) were identified utilising the BOA technique taking into account the peculiarities of the aforementioned activity traces: a, b, and c. It is therefore feasible to create a dataset that includes the gathering of each of the event-driven & trace-level characteristics by taking into account both of the current trace-level characteristics, et and pc. In this manner, the procedure's control-flow and information properties may be examined to one another. In order to connect to the element which serves as the foundation for verifying deviant behaviour, the given name for an attribute of a class (c_{name}) has to be identified in the dataset. The term " c_{name} " must be used to identify a trace-level performance marker that is relevant for examination. False-valued (unsuccessful) footprints are regarded as aberrant instances in our scenario since the effective completion characteristic is specified as a class variable, c_{name} = pc.

A. Mining Declare Constraints as Trace-level Attributes

Compared to the currently used series encoding methods, they also suggest a fresh method employing logical process mining in order for extracting traits from periods of happenings. They took into account the Declaration programming syntax and its restriction examples, which offer the primary relationship and presence restrictions forms. They took into account the meaning of Declare restrictions using standard patterns included in both Unrestricted Miner and MINERFul++ declaratory mining algorithms with the goal to execute the discovery of limitations at the track levels. They must stay away from vacuously fulfilled restrictions since pattern fulfilments are the things that we want to engage in. To eliminate simply met restrictions, a different labelling collection of support automaton for vacuity detecting is suggested. In our search process, the comparable routine expressions used by the vacuity detecting support automata have been taken into account. Declarative syntax mining methods now in use seek to identify a collection of restriction patterns to describe the behaviour of a whole event record as one procedure paradigm. To determine if a restriction template is valid and meaningful, these techniques may take into account several threshold characteristics at the event log level, such as support, confidence, and interest factor. Through examining the achievement of a set Announce specifications for every step in the trace, they hope to employ Declare constraints as features at the trace level in this study. Similar to the previously discussed current encoding methodologies, those Declare-based attributes for each process trace may be used to create a collection of examples.

They use declaratory procedure mined approaches to identify whether Declaration requirements was satisfied in every programme tracing $h \in H$, provided an events log P. A number of Predefined limitations have to be established before mine can be done correctly. A Declaration restriction generators collection may represent all of it or a portion of it in this case. It then needs to be paired to a collection of unique occurrences that are recorded on the occurrence log. This occurrence set includes the parameters that Declaring requirement patterns require in order to function, while this mixture produces the collection of characteristics produced by this encode technique. By creating unique ordinary expressions, the list of default requirement templates may be expanded to include additional restrictions as appropriate. The label of the restriction example, that symbolises an abstraction of a restriction (at first used stated in LTL or via an ordinary expressions), plus a group of parameters are combined to form a Declare restriction d, where d = name ({args}). The total amount of parameters differs based on the pattern; for instance, a init restriction theme only requires a single query since it applies to the occurrence who initiates the trace's execution, but the coexisting restraint pattern requires two inputs because it applies whenever two occurrences occur in the same processes trail.

Considering the occurrence logging instance P ′ from earlier, that includes a collection of three separate occurrences (a, b, and c). Three Declaration requirements init (a), init (b), and init (c) can be produced from a Declaration restriction generator of class init. Every limitations, represented by "1" as a fulfilment or "0" alternatively, makes up as a trace-level attribute-value pairing in the sake of decoding by obtaining an amount matching to the Declaring condition's fulfilment. Common attribute-value pairings associated with the $init$ model, for instance, are as follows: $h'_{attr=((init(a),1),(init(b),0),(init(c),0))}$. The exactly_n model, which counts an exact n of instances of events within the entire track, corresponds to the lone alternative. Activity tracing containing Declare-based attribute-value pairings can then be converted into database objects in a manner similar to that shown in the table for boa coding. A typical dataset is shown in Table III and is made up of objects with characteristics that correspond to an example of Declaration restrictions obtained from the event log P ′. Declare-based characteristics may represent timing connections among actions in a manner that sequence- based set-based encoding methods can't, in contrast with other current encoding methods. For instance, the boa, bigram, mra, and mrs methods do not have an equivalent for the answer (b,c) restriction. Customised constraints for incident sequencing representations of features may nevertheless be defined. Declaring also offers a number of predefined templates that can handle a variety of timing connections between procedure incidents, which is a further advantage. Concerning methodology, each of the four rules may be represented with the current Announce limitation components.

TABLE III. EVENT LOG USING DECLARE ENCODING

h_{id}	Init(x)	Last(x)	Exactly(x)	Response(x,y)	et	pc
h_1	1	0	2	1	4.5	false
h_2	1	1	2	0	3.2	true
h_3	1	1	3	1	7.3	false

B. Machine Learning Evaluation

1) Standardized stream flow index (SSI): Similarly to indicators of severe weather, the majority of investigations used standardised criteria for assessing hydrologic dryness. Two significant standardised indices are flow indices and standardised runoff indices, both which have an analogous theoretical foundation. The sole difference between SSI computations and other computations is that run-off from the surface data are utilised in place of precipitation data. For example, this index displays correct beta dispersion. As a result, for each month, the total flow values are separately estimated before the SSI is computed.

2) Gene Expression Programming (GEP): Genetics can be made using genetic algorithms in the Gene Expression Programming (GEP) algorithm, which uses communities of people and selects these according to fitness. The GEP method's initial step is to create a main collection of answers. This level can be finished by an unintentional procedure or by using some knowledge about the issue. The chromosomal structures were then visualised as a tree expression and evaluated using a fitting method. In general, processing a number of target issues, also known as fitting problems, allows for the evaluation of the appropriate function. The research process ends and the most effective resolution is determined once the answer has an appropriate standard or if a certain number of iterations have passed. The most suitable response form the latest generation is maintained if the most favourable scenario cannot be discovered, and the remaining options are left to be chosen from. The best people are more likely to have children, based on the decision. For many generations to come, every step has been repeated, and it is anticipated the group in question quality will generally increase as new generations are born. GEP chooses the candidates using the renowned roulette wheel approach. In contrast to genetic algorithms and genetic programming, GEP uses a number of genetic operatives to reproduce modified people. Replica is a procedure designed for preserving a few of the most talented members of this era into the following one. A mutation operator's objective is to insert arbitrary changes into an individual chromosome. To avoid producing people deemed rule-deficient, this operator conducts some of the perfect procedures. GEP employs a one-point and two-point combination, similar to a biological algorithm. The genomic equivalent problem (GEP) employs a single-point and two-point combinations. The kind of two-point combo is a little more intriguing because it can largely switch on and off the chromosomal regions that are not encoded. Additionally, the GEP also performs a different kind of combining known as gene combination, in which genes are entirely combined. To create two new children, this operator randomly chooses genes on both-parent chromosomes that are located in the same location.

C. *Support Vector Regression*

Over the following decades, Support Vector Machine (SVM) evolved into a linear classification algorithm using optimum hyper plane concept. Utilising statistical learning theory, this approach is used. Additionally, they utilised kernel algorithms to create nonlinear classifications. SVM's classification algorithm serves to categorise problems associated with data into multiple classes, while its regression technique is applied to solve prediction issues. Regression on fit data produces a hyper plane. A given location's deviation from its hyper plane revealed the inaccuracy of that location. The most effective technique for regression analysis is advised is the least squares approach. But it can happen that using a least-square estimation for analysis issues in the form of outliers may not be entirely rational, which would lead to the analysis performing poorly. In order to avoid bad performance that is not responsive to minute modifications to the model, a robust estimator should be created. As mentioned, the SVM is built upon the principle of minimising risk, a hierarchy generated by the theory associated with statistical training. a distance from real values termed an error function to employ SVM in regression issues that overlook mistakes in a -insensitive manner. This function's definition translates as follows in Eq. (1) and Eq. (2):

$$P(a, f(d,y) = \left|a - f(d,y)\right|_{\varepsilon} \tag{1}$$

$$= \begin{cases} 0 \quad for\ \left|a - f(d,y)\right| \leq \varepsilon \\ \left|a - f(d,y)\right| - \varepsilon\ if\ \left|a - f(d,y)\right| > \varepsilon \end{cases} \tag{2}$$

Below, this mistake function does not take into account errors.

D. *M5 Model Tree*

This technique is an amalgam of machine learning and data mining techniques. Data mining techniques identify several, suitable frameworks before extracting data from a pool of set values. Because data mining techniques differ from statistical approaches because they were established for huge datasets with multiple variables, they were created for smaller datasets with fewer variables. Among the most popular data mining approaches, decision tree-based methods use input data to forecast or categorise target qualities as an output in the shape of an equation having a structure of trees. The M5 modelling trees are a structure of choices that may be utilised for forecasting continuous quantitative qualities. Its branches are representations of regression operate, and it has lately sparked a substantial development in classifications and predictions. When contrasted to other theories, the tree algorithm's data has higher precision and is simpler to replicate and comprehend. A tree of choices is composed of four components: the root, the branch, the nodes, and the leaves. The rectangular shape denoted each node, while the connections between them were shown as branches. The tree of choices usually goes from left to right or from top to bottom, with the base (first node) on the very top to make it easier to create. The leaf denotes the conclusion of a series of events. For the reason of minimising the total of the squared variances from the average information for each node, splitting is carried out by one of the predictive variables. Utilising the splitting criterion is the first step in creating a tree model. The M5 algorithm's dividing criteria relies on the accuracy of the usual variation of the numbers acquired in every node that correspond to every class or subcategory. In a consequence of checking every characteristic at that node, dividing criteria determines the amount of erroneous for that component and determines the smallest predicted error type. In most circumstances, the predictive inaccuracy is determined by assessing how well the desired outcomes for hypothetical cases are predicted. SDR, or standard deviation reduction, is given in Eq. (3).

$$SDR = sd(H) - \sum \frac{\left|H_i\right|}{\left|T\right|} sd(H_i) \tag{3}$$

The total number of specimens approaching all nodes is shown by H, and H_i is the portion of examples which correspond to the nth outcome of a possible test. sd stands for standard deviation. Up till reaching the final cluster (the leaf), the method of division is repeated multiple times at every node. So when it reaches the leaves, the total of the squared differences above the average information is virtually zero. The consequence is going to be the growth of a huge tree. Using numerous limbs and nodes, it is going to difficult to operate using this large tree; as a result, undesirable branches must be removed to create an ideal and effective tree. There are a total of two ways to prune: (1) while the plant forms its full potential, (2) trimming following the peak of shrub development. The second strategy begins by forming the largest possible tree before beginning the trimming manipulate, unlike the initial method, which prevents the tree from growing further branching. Choosing the best branch is dependent on reducing errors in prediction.

E. *Evaluation parameters*

The root mean square error (RMSE) (4), relative absolute error (RAE) (7), mean absolute error (MAE) (5), and correlation coefficient (CC (6)) were used to analyse the error values between the anticipated and observed data.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i - a_i)^2} \quad (4)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|d_i - a_i\right| \quad (5)$$

$$CC = \frac{(\sum_{i=1}^{n} d_i a_i - \frac{1}{n}\sum_{i=1}^{n} d_i \sum_{i=1}^{n} a_i)}{(\sum_{i=1}^{n} d_i^2 - \frac{1}{n}(\sum_{i=1}^{n} d_i)^2)\,(\sum_{i=1}^{n} a_i^2 - \frac{1}{n}(\sum_{i=1}^{n} a_i)^2)} \quad (6)$$

$$RAE = \frac{\sum_{i=1}^{n}\left|a_i - d_i\right|}{\sum_{i=1}^{n}\left|d_i - \bar{d}\right|} \quad (7)$$

When n represents the total amount on assessments, and xi, yi are the anticipated & observed results of the SSI. Complete correlation (CC) among measured and anticipated numbers. Correlation that is direct is shown by values that are positive, and the opposite relationship is indicated by negative values. Additionally, the RMSE and MAE values are errors, therefore smaller values suggest lesser modelling mistakes.

V. Results and Discussion

The effectiveness of the three models—SVM, GEP, and M5—in projecting the Standardised It Index utilising the SPI and SPEI indices at Navrood station throughout six-time delays (a one-month to six-month) is examined in the current work. A 48-month grade was chosen for investigation in this study out of the several scales for predicting SSI since it had a stronger correlation and was predicted by the mathematical models that were provided. The statistical characteristics of the drought indices used in the research region are shown in Table IV.

TABLE IV. Statistical Characteristics of the Utilized Data

SSI	skewness	coefficient of variation	standerd deviation	maximum	minimum	mean	variable
0.69	0.13	958.7	0.98	1.98	-2.09	0.0011	SPI
0.69	-0.69	19.098	0.99	1.45	-2.023	-0.054	SPEI
1	0.08	530	0.99	1.98	-1.67	0.003	SSI

The Fig. 2 shows the Root Mean Square Error (RMSE) values for three machine learning algorithms: GP, M5, and SVR. Each row represents a different evaluation scenario or experiment. The values indicate the accuracy of the algorithms, with lower RMSE values indicating better accuracy. Based on the table, GP consistently has the lowest RMSE values across different scenarios, suggesting it performs better than M5 and SVR in terms of accuracy.

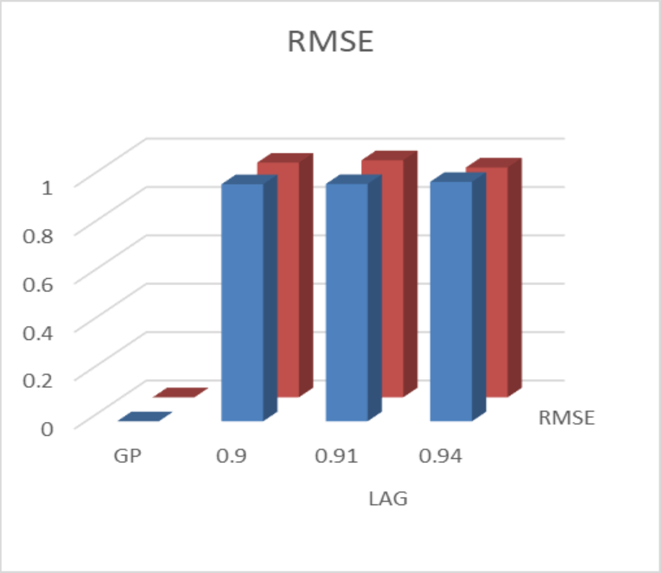

Fig. 2. RMSE model.

The Fig. 3 represents the Mean Absolute Error (MAE) values for three machine learning algorithms: GP, M5, and SVR. Each row corresponds to a different evaluation scenario. MAE is a metric used to measure the average absolute difference between the predicted and actual values, where lower values indicate better accuracy. Based on the table, GP consistently has the lowest MAE values across different scenarios, indicating it performs better in terms of accuracy compared to M5 and SVR.

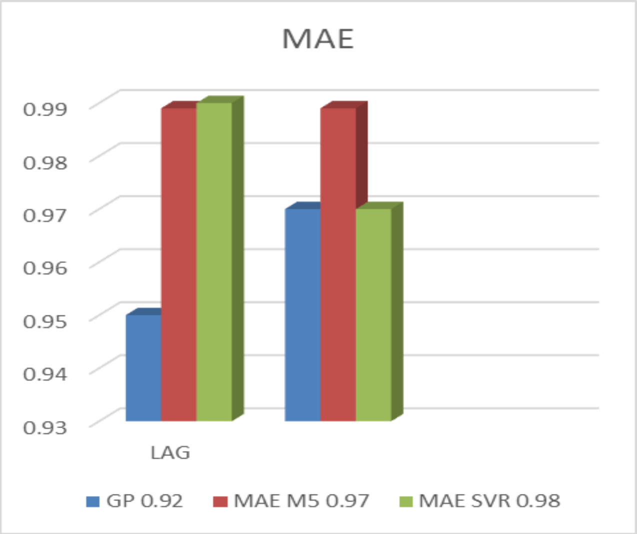

Fig. 3. MAE model.

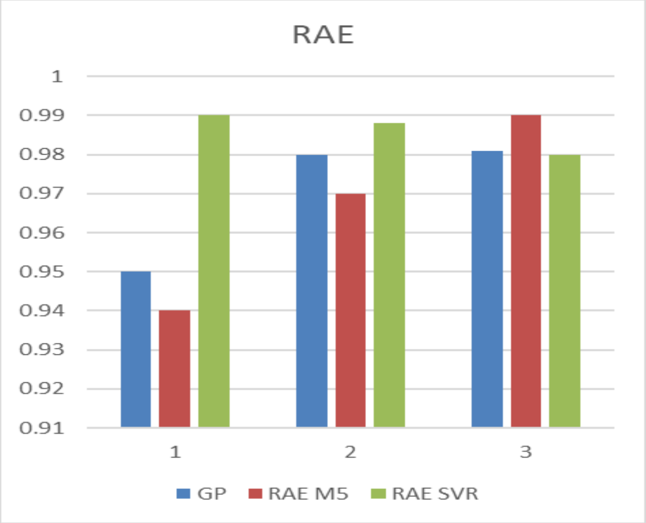

Fig. 4. RAE model.

The Fig. 4 shows the Relative Absolute Error (RAE) values for three machine learning algorithms: GP, M5, and SVR. Each row represents a different evaluation scenario. RAE is a metric used to measure the relative difference between the predicted and actual values, indicating the performance of the algorithms in relation to the magnitude of the target variable. Lower RAE values indicate better accuracy. Based on the table, GP generally has lower RAE values across different scenarios, suggesting it performs better in terms of accuracy compared to M5 and SVR in relation to the magnitude of the target variable.

Additionally, determined by Pearson's correlation but cross-correlation, it was determined that the USDA hydrological dryness index was better and predicted with a smaller error even though the drought index is better and more dependent on climatic circumstances.

TABLE V. PERFORMANCE METRICS COMPARISON

Method	Standard Deviation
SVM [20]	0.9
MLP[21]	0.6
MLP[22]	0.6
Proposed Method	0.9

A comparison of performance measures, namely standard deviations, for various approaches is shown in Table V. The Support Vector Machine (SVM) shows performance variability with a standard deviation of 0.9. Two presentations of the Multilayer Perceptron (MLP) technique are made; in both cases, the standard deviation is 0.6, indicating higher consistency in performance as compared to SVM. Interestingly, the suggested technique, which makes use of Support Vector Regression (SVR), has a standard deviation of 0.9, which is consistent with the variability shown in SVM. These measures provide insights into the stability and reliability of each method, with lower standard deviations often reflecting more consistent performance.

VI. CONCLUSION

The research contributes significantly to the domain of commercial operation divergence analysis, offering valuable insights into the identification of variations in commercial systems beyond anticipated outcomes. By delving into the characteristics of procedure executions, the study illuminates' behaviours impacting process efficiency, encompassing both detrimental and optimal aspects. Success in this context is gauged through domain-specific efficiency metrics, encompassing cost-effectiveness, time optimization, and resource utilization. Users may have concerns regarding the dependability and efficacy of machine learning models in detecting and mitigating threats in applications like cyber security or automated threat detection. It's critical to fully assess the models' performance using real-world data and stringent testing protocols in order to address this. Moreover, adding human supervision to the machine learning procedure might offer still another level of security. Clearly defined procedures for human evaluation and intervention, particularly in crucial decision-making roles can guarantee responsibility and reduce the hazards connected with automated systems. The paper introduces an innovative decoding strategy that utilizes Declare constraint templates, enabling more expressive treatments through vector-based representations of procedure scenarios. Additionally, the research pioneers the application of Machine Learning, incorporating algorithms like Standardized Stream flow Index, Gene Expression Programming, Support Vector Regression, and M5 Model Tree within the realm of Deviance Mining. This approach effectively identifies the aspects of a procedure significantly influencing its efficiency, surpassing traditional trend mining methods to handle intricate linkages within highly variable systems. The experimental outcomes underscore the efficacy of machine learning when integrated with the proposed Declare-based coding. Analysing event logs through this approach yields pertinent and insightful conclusions, offering a comprehensive understanding of process behaviour and performance. While acknowledging these contributions, it is crucial to recognize the limitations of the current study, such as the specific contextual constraints and the need for further validation across diverse industry scenarios. Future work in this field by iteratively validating the model's performance across various data partitions, cross-validation provides a more robust estimate of its generalization ability, helping to identify and address over fitting issues before deployment in real-world scenarios. This research sets the stage for practical and effective tools in process analysis, empowering organizations to make informed, data-driven decisions for optimizing efficiency, reducing costs, and enhancing overall performance.

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Utilizing Federated Learning for Enhanced Real-Time Traffic Prediction in Smart Urban Environments

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Abstract—**Federated Learning (FL), a crucial advancement in smart city technology, combines real-time traffic predictions with the potential to enhance urban mobility. This paper suggests a novel approach to real-time traffic prediction in smart cities: a hybrid Convolutional Neural Network-Recurrent Neural Network (CNN-RNN) architecture. The investigation started with the systematic collection and preprocessing of a low-resolution dataset (1.6 GB) derived from real-time Closed Circuit Television (CCTV) traffic camera images at significant intersections in Guntur and Vijayawada. The dataset has been cleaned up utilizing min-max normalization to facilitate use. The primary contribution of this study is the hybrid architecture that it develops by fusing RNN to detect temporal dynamics with CNN for geographic extraction of characteristics. While the RNN's recurrent interactions preserve hidden states for sequential processing, the CNN efficiently retrieves high-level spatial information from static traffic images. Weight adjustments and backpropagation are used in the training of the proposed hybrid model in order to enhance real-time predictions that aid in traffic management. Notably, the implementation is done with Python software. The model reaches a testing accuracy of 99.8% by the 100th epoch, demonstrating excellent performance in the results and discussion section. The Mean Absolute Error (MAE) results, which show a 4.5% improvement over existing methods like Long Short Term Memory (LSTM), Support Vector Machine (SVM), Sparse Auto Encoder (SAE), and Gated Recurrent Unit (GRU), illustrate the efficacy of the model. This demonstrates how well complex patterns may be represented by the model, yielding precise real-time traffic predictions in crowded metropolitan settings. A new era of more precise and effective real-time traffic forecasts is about to begin, thanks to the hybrid CNN-RNN architecture, which is validated by the combined strengths of FL, CNN, and RNN as well as the overall outcomes.**

Keywords—Federated Learning; smart city; convolutional neural network; recurrent neural network; traffic prediction

I. Introduction

Federated Learning which tackles privacy issues and decentralizes model training, is a paradigm shift in machine learning. Due to the transmission and storage of sensitive data, traditional machine learning models are frequently trained on centralized servers using aggregated datasets, which raises privacy concerns [1]. Conversely, Federated Learning enables cooperative model training across decentralized devices, such as servers, edge devices, and smartphones, without requiring raw data exchange [2]. This novel method preserves the privacy of local data while enabling individual devices to make improvements to the model. Federated Learning is a tempting option for applications in healthcare, finance, and, most importantly, the setting of smart cities. It is especially applicable in situations where data privacy is a top priority [3].

The integration of technology to improve urban living is a hallmark of smart cities, and federated learning is essential to this shift. It is clear that efficient and private-preserving machine learning solutions are needed in the context of smart cities, where enormous volumes of data are produced on a regular basis from many sources [4]. Smart city applications that make use of Federated Learning may train models collaboratively with data from disparate sensors, devices, and systems dispersed across the city. This method is especially applicable to situations where precise decision-making requires the aggregation of real-time data, such as energy management, pollution monitoring, and traffic prediction [5].

Because Federated Learning is decentralized and keeps data localized, it naturally addresses privacy issues. To protect contributor privacy, only model changes are shared rather than raw data that is sent to a central server. This is particularly important in smart cities, where there is a need to manage data from several sources carefully, such as public databases, IoT devices, and security cameras [6]. In order to guarantee the safe and private transmission of model changes, Federated Learning also uses cryptographic methods and secures aggregation protocols. Federated Learning is a desirable alternative for implementing machine learning solutions in the delicate and changing contexts of smart cities because of these privacy and security constraints.

Federated Learning presents problems in addition to its many appealing benefits. Non-trivial problems include coordinating model updates from a variety of devices, handling heterogeneous data sources, and controlling communication overhead. Through breakthroughs like federated optimization algorithms, model compression approaches, and effective communication protocols, researchers and practitioners are actively attempting to overcome these difficulties [7]. Federated Learning will be more effective, scalable, and suitable for a larger range of smart city use cases thanks to these developments. Federated Learning is becoming more and more popular in smart cities, as seen by practical uses. Decentralized machine learning is helping smart cities anticipate traffic patterns, optimize waste management, and improve public safety. Success tales emphasize decreased latency, increased prediction accuracy, and above all the protection of citizen privacy. Federated Learning is positioned to be a key player in creating data-driven and privacy-preserving urban ecosystems as smart city programmes continue to grow [8].

Federated Learning has a bright future in smart city applications. Federated Learning is anticipated to become an essential component in the creation and implementation of intelligent systems as technology develops and the need for privacy-preserving solutions increases. The responsible and ethical deployment of Federated Learning in smart city contexts will depend heavily on the cooperation of academics, business, and government in tackling the remaining obstacles. Federated Learning stands out as a critical enabler as cities work to become more interconnected, effective, and sustainable [9]. It provides a means of using the combined intelligence of dispersed data sources while preserving people's security and privacy in urban areas. Smart cities are metropolitan regions that use data and technology to improve the effectiveness and standard of urban living. Cities must manage intricate systems like transit as the globe grows more urbanized in order to provide smooth movement for its citizens. Improving overall urban mobility, streamlining transport networks, and lowering congestion all depend heavily on real-time traffic forecast. The dynamic nature of urban areas presents challenges for traditional approaches of traffic prediction. Using cutting-edge technology like Federated Learning has become a viable strategy to solve these issues.

For efficient urban planning and administration, traffic prediction is essential. It makes it possible for local government officials to improve public transport services, optimize traffic signal timings, and proactively handle traffic congestion. Individual commuters can also benefit from real-time traffic data, which can assist them in making well-informed decisions regarding their travel schedules and routes. Predictive models allow smart cities to be proactive in addressing traffic problems, lessening their negative effects on the environment, and improving the general quality of life for their citizens [10]. By using a decentralized machine learning technique called federated learning, models may be trained on many servers or devices without requiring the exchange of raw data. Federated Learning is an innovative approach for privacy and data security in the context of smart cities. Without jeopardizing personal privacy, traffic data from several sources including sensors, GPS units, and cameras can be used to train models. Through collaboration, heterogeneous statistics from various sections of the city are leveraged to create strong and reliable traffic forecast models.

Federated Learning has many benefits, but there are drawbacks as well. It takes significant planning to coordinate and aggregate models from many places while upholding data security and privacy. Federated Learning implementation in real-time traffic prediction also requires eliminating potential biases and guaranteeing the interoperability of heterogeneous datasets. But there are also a lot of potential since this strategy enables cities to use the combined wisdom of disparate data sources to create traffic forecast models that are more precise and flexible [11]. Several smart cities worldwide have already started exploring the potential of Federated Learning for real-time traffic prediction. Case studies illustrate the successful implementation of this technology, showcasing improvements in traffic flow, reduced congestion, and enhanced transportation services. These examples serve as inspiration for other urban centers seeking innovative solutions to address their unique traffic management challenges. As smart cities continue to evolve, the integration of Federated Learning for real-time traffic prediction holds great promise [12]. The future implications extend beyond traffic management to contribute to a broader vision of sustainable and intelligent urban living. Cities can address existing transportation difficulties and provide the groundwork for a more connected, efficient, and resilient urban future by embracing cutting-edge technology like Federated Learning. The success of smart cities is largely determined by the cooperation of technology, data science, and urban planning; a crucial element of this revolutionary process is real-time traffic forecast.

The research questions for utilizing federated learning for enhanced real-time traffic prediction in smart urban environments may include:

- How can federated learning algorithms be adapted or optimized to effectively leverage distributed data sources for real-time traffic prediction in dynamic urban environments?
- What strategies can be employed to address privacy concerns while aggregating and learning from decentralized traffic data in federated learning settings?
- How can federated learning models be integrated with existing traffic prediction systems to enhance accuracy and reliability in smart urban environments?

The research objectives could be:

- To investigate and analyze existing federated learning algorithms and assess their suitability for real-time traffic prediction tasks.
- To develop novel techniques for privacy-preserving federated learning in the context of traffic prediction, ensuring compliance with regulatory standards and user privacy preferences.
- To design and implement a federated learning framework that integrates seamlessly with urban traffic monitoring systems, enabling real-time data exchange and model training across distributed nodes.

The research significance lies in its potential to revolutionize traffic prediction systems in smart urban environments by leveraging federated learning techniques. By addressing privacy concerns and enabling decentralized model training, this research could pave the way for more accurate, efficient, and scalable traffic prediction systems that can adapt to the dynamic nature of urban environments. Furthermore, the outcomes of this research could have broader implications for the development of federated learning applications in other domains, contributing to advancements in decentralized machine learning and data privacy preservation.

The key contributions of the paper are given as follows:

- The study presents unique hybrid architecture for real-time traffic prediction in smart cities that combines CNN and RNN. This combination of techniques incorporates the best aspects of temporal analysis from RNN, which identifies sequential patterns and relationships in traffic data with spatial evaluation from CNN, which identifies high-level characteristics from static traffic images.
- In contrast to traditional models, the suggested method combines geographical and temporal components for traffic prediction. While the CNN module retrieves static geographical information to provide an extensive understanding of traffic patterns, the RNN component methodically examines sequential data, taking into account unpredictable shifts in traffic circumstances over time.
- The study proposes a paradigm that improves privacy and efficiency by utilizing the concepts of federated learning. The federated learning strategy guarantees decentralized learning, protecting the privacy of individual sources of information while jointly enhancing the global model, by permitting local training on customer devices with locally produced data.
- To maximize the model's performance, the hybrid model uses backpropagation-based training and weight modification techniques. In the end, this increases the accuracy of real-time traffic forecasts by allowing the network to adjust to complicated temporal correlations and geographical patterns in traffic information.
- The suggested architecture is mostly used in the field of smart city traffic management. The model enhances road safety in urban contexts, reduces congestion, and improves traffic flow efficiency by improving real-time traffic forecast skills. The suggested model stands out as a complete response to traffic issues in smart cities due to its holistic approach, which takes into account both static and dynamic elements.

The arrangement of the remaining content is as follows. The traffic prediction literature is illustrated in Section II. The Problem Statement is provided in Section III. The suggested method for predicting traffic in real-time in smart cities is discussed in Section IV. In Section V, the method's performance is compared to earlier approaches, and the performance measurements are illustrated along with a summary of the findings. The conclusion and future works is summarized in Section VI.

II. RELATED WORKS

The widespread use of Internet of Things (IoT) sensors and devices, in conjunction with artificial intelligence, has resulted in the creation of "smart environments [13]." However, these solutions have high latency conditions and more information transmission from a network standpoint. Accordingly, this paper suggests a Federated Learning structure for Real-Time Traffic Calculation, which is supported by Roadside Units for simulation aggregation. The solution envisions learning being done on clients with locally generated information, and fully dispersed on the Edge, with outstanding learning rates, low latency, and less bandwidth consumption. To that end, this paper addresses tools and necessities for FL implementation towards asynchronous traffic estimation, as well as how such an approach could be assessed employing VANET and network simulations. The study first provides a preliminary assessment of a learning model on a group of automobiles that exemplify a distributed learning technique as a practical step. The study intends to employ a distributed technique like to this one in our proposed design. It is necessary to talk about the suggested solution's suitability in situations when vehicular ad hoc networks aren't present. The study should examine the approach's flexibility given that not all places may have a substantial VANET infrastructure.

Since federated learning is decentralized and protects data sources' privacy, it is commonly used in traffic forecasting employment requiring large-scale IoT-enabled sensor data. The current FL frameworks face significant overhead in communication when transmitting changes to parameter values for state-of-the-art deep learning-derived traffic indicators in FL systems, as the models' extensive and deep modelling necessitates the incorporation of a large number of parameters. To address this issue, we provide in this paper a workable FL scheme: Clustering-based modular and Two-step-optimized FL [14]. The suggested plan uses a divide et impera technique to categorize the clients according to how comparable the parameters of their local models are. Researchers include the particle swarm optimization technique and develop a two-phase method for optimizing local models. This technique lowers the communication cost of the model update transmission in FL by allowing just one representative local model upgrade from each cluster to be published to the central server. In order for the gradient compression or sparsification-based techniques to coordinate and minimize communication cost, CTFed is perpendicular to them. Comprehensive case studies utilizing three real-world sets of information and three cutting-edge models show how the suggested approach excels in terms of training effectiveness, precise forecasting performance, and resilience to unstable network settings. The suggested scheme's scalability, however, could have drawbacks. In large-scale IoT-enabled networks of sensors, in particular, the number of clients can lead to computationally demanding clustering and optimization stages that compromise scalability.

Recent developments in cloud computing, which offer near real-time processing along with storage scalability, have accelerated the development of data-intensive smart city applications. Millions of people rely on centralized, effective route planning systems like Google Maps as a result of this. Algorithms for route planning have advanced along with the cloud settings in which they operate [15]. As current state-of-the-art solutions are predicated on a shared memory paradigm, their deployment is constrained to data center multiprocessing scenarios. As a result of centralizing these functions, latency is becoming the limiting factor for emerging technology like driverless vehicles. These services also need connectivity to external networks, which raises questions about availability in the event of a disaster. As a result, this study offers a decentralized method for commercial fog network route planning. The study uses a hypothetical case study from a mid-sized American city to explore our method of cooperatively learning shared prediction models online, using recent breakthroughs in federated learning. However, a number of variables, such as network congestion, device malfunctions, and environmental circumstances, might affect the dependability and accessibility of private fog networks. The article ought to go into how the suggested strategy handles these kinds of obstacles.

Intelligent transportation systems, particularly in urban settings, are undergoing a transformation as a result of the Internet of Things' exponential expansion [16]. Transport network intelligence and efficiency are improved by an Intelligent Transportation System by utilizing data analytics and communication technology innovations. These IoT-enabled ITSs also produce a large amount of complicated data that is categorized as Big Data. Due to the enormous volume, velocity, diversity, and serious data privacy problems associated with Big Data, traditional information analysis frameworks require assistance in order to analyze it effectively. Federated Learning, which is well-known for protecting privacy, is a promising technique that may be used in ITSs to handle Big Data created by IoT devices. However, the variety of data, the varying nature of devices, and the dynamic environment in which ITS functions provide difficulties for the system. The concrete selection of an averaged technique during the server's aggregation phase and the practical training of dynamic clients are the main areas of recent endeavour to address these difficulties. The research that is now available, notwithstanding these efforts, still depends on customized FL with customized averages and customer education. In this study, a tailored architecture utilizing FL for effective and real-time large-scale data analysis in IoT-enabled ITSs is presented, along with an efficient Federated Averaging technique. The conventional averaging process is improved by applying a variety of customizing techniques. Weighted averaging and local fine-tuning adapt the global algorithm to the unique client data. Further performance improvement is achieved by using custom learning rates. To keep the model's efficacy intact, regular assessments are recommended. The suggested architecture provides a complete solution for contemporary urban transportation systems utilizing Big Data, addressing important issues including actual existence federated environment applications integrating information, and substantial data protection. The study implements the suggested methods for vehicle detection on the Udacity Self-Driving Car Database to show our model's effectiveness. The empirical findings confirm the architecture's superiority in terms of data privacy protection, instantaneous decision-making capabilities, and scalability.

Since sharing confidential information puts people's lives in danger, privacy concerns are seen as one of the biggest obstacles in smart cities. Federated learning has shown to be a successful method for both protecting privacy and optimizing data usage [17]. However, the amount of identifiable information acquired in smart cities is limited, while the amount of unlabelled data produced is abundant; this makes the use of semi-supervised learning necessary. We suggest FedSem, a semi-supervised collaborative learning technique that makes use of unlabelled data. The technique is split into two stages, the first of which uses the labelled data to train a global model. To enhance the model in the second stage, the study employs semi-supervised learning depending on the pseudo labelling approach. Utilizing the traffic sign dataset, the study ran a number of tests to demonstrate how FedSem may use unlabelled information to enhance accuracy throughout the procedure of learning by a maximum of eight percent.

Over the next several decades, Artificial Intelligence will revolutionize many aspects of our lives and careers, from face recognition to autonomous driving. Current AI methods for urban computing face several obstacles, such as managing the processing and synchronization of massive amounts of data created by edge devices and protecting user privacy and security, including biometrics, geolocation, and itinerary data [18]. Conventional centralized-based methods need uploading all organizational data to a single database, which may be against the law according to data protection laws like the CCPA and GDPR. Federated Learning, a novel training paradigm, is suggested as a way to separate model training from the requirement to keep the data on the cloud. With FL, the danger of privacy leakage may be greatly reduced as several devices can work together to jointly build a common framework while retaining the training data locally on each device. However, data in urban computing situations are frequently asynchronous, high-frequent, and communication-heavy, which presents additional difficulties for the implementation of FL. The study suggests StarFL, a novel hybrid federated learning architecture, as a solution to these problems. Secure key distribution, encryption, and decryption are made possible by StarFL in conjunction. Additionally, StarFL offers a verification method for every participant to guarantee the confidentiality of the local data. Furthermore, StarFL can offer precise timestamp matching to make it easier for several clients to synchronize. With all of these enhancements, StarFL is now more suitable for use in security-sensitive circumstances in the upcoming urban computing age.

Through decentralized training initiatives, federated learning has already been utilized for a variety of activities in automated transportation systems to preserve data privacy [19]. When it comes to learning spatial information, most of the most sophisticated approaches in automated transportation systems depend on graph neural networks. The present architectures for federated learning in ITS activities utilizing GNN-based models are limited to safeguarding data privacy, and they fail to consider the topological data related to transportation systems. To address this issue, the study presents a unique architecture for federated learning in this study. To safeguard the topological information, the study specifically presents an adjacency matrix preservation method that employs differential privacy. Additionally, the study suggests using an adjacency matrix aggregation technique to provide local GNN-based models access to the global network for improved training outcomes. Additionally, the study suggests the attention-based spatial-temporal graph neural networks model for traffic speed forecasting, which is based on GNNs. For traffic speed forecasting, we combine ASTGNN as FASTGNN with the suggested federated learning system. Numerous case studies using an actual dataset show that FASTGNN is capable of producing precise forecasts while adhering to the privacy preservation requirement.

The fields of real-time traffic estimates and smart city applications have already investigated a number of approaches, such as graph neural networks, semi-supervised learning, and federated learning. Federated learning has proven successful in maintaining privacy, whereas FedSem and other semi-supervised learning techniques have tackled the difficulties associated with using unlabelled data. Transportation systems have used graph neural networks to extract topological information. But these methods frequently run into problems, such scalability problems in large-scale IoT networks, communication overhead, and dependence on specialized federated learning methods. Furthermore, difficulties with data synchronization, privacy issues, and processing needs have been identified. In order to overcome these drawbacks, the research suggests a hybrid CNN-RNN approach to real-time traffic prediction. This model seeks to improve precision as well as effectiveness in smart city traffic management by utilizing the advantages of both spatial as well as temporal analysis.

The proposed utilization of FL for real-time traffic prediction in smart urban environments holds significant promise, addressing issues of privacy preservation and scalability inherent in centralized models. However, several limitations and challenges need to be considered. Firstly, the scalability of FL frameworks, particularly in large-scale IoT-enabled networks, may be compromised due to computational demands during clustering and optimization stages. Additionally, while FL offers privacy protection, the decentralized nature of urban computing environments presents asynchronous, high-frequency, and communication-heavy data, posing challenges for FL implementation. Moreover, existing FL architectures may not adequately address topological data related to transportation systems, necessitating innovative approaches for preserving such information while ensuring privacy. Furthermore, the effectiveness of FL techniques may be impacted by variables such as network congestion, device malfunctions, and environmental circumstances, which could affect the reliability and accessibility of FL-based traffic prediction systems. Thus, future research efforts should focus on addressing these limitations to realize the full potential of FL in enhancing real-time traffic prediction in smart urban environments. Table I shows the advantages and disadvantages of existing methods.

TABLE I. ADVANTAGES AND LIMITATIONS OF EXISTING APPROACHES

Authors	Methods	Advantages	Limitations
M. V. S. da Silva, L. F. Bittencourt, and A. R. Rivera,	Utilizes FL for real-time traffic prediction, supported by Roadside Units for simulation aggregation. Learning done on clients with locally generated data, dispersed on the Edge, with low latency and less bandwidth consumption.	Decentralized model training enhances privacy protection. Scalability due to distributed nodes.	Computational demands in large-scale networks may compromise scalability. Challenges with data synchronization and communication overhead.
C. Zhang, L. Cui, S. Yu, and J. J. Q. Yu,	Uses divide et impera technique to categorize clients based on local model parameters. Incorporates particle swarm optimization and two-phase optimization for local models, reducing communication costs.	Reduction in communication overhead. Effective training and precise forecasting performance. Resilience to unstable network settings.	Computational demands during clustering and optimization may affect scalability.
M. Wilbur, C. Samal, J. P. Talusan, K. Yasumoto, and A. Dubey	Hybrid federated learning architecture with secure key distribution, encryption, and decryption. Offers verification method for data confidentiality and precise timestamp matching for synchronization.	Enhanced security and privacy protection. Precise timestamp matching improves data synchronization.	Complexity in implementation and management. Potential performance overhead due to encryption and decryption processes.
S. Kaleem, A. Sohail, M. U. Tariq, and M. Asim,	Tailored architecture for real-time data analysis in IoT-enabled ITSs. Improves conventional averaging process with customizing techniques like weighted averaging, local fine-tuning, and custom learning rates.	Improved data privacy protection and model effectiveness. Scalability with efficient customization techniques.	Complexity in customization and management. Potential performance overhead due to customization processes.
A. Albaseer, B. S. Ciftler, M. Abdallah, and A. Al-Fuqaha,	Utilizes both spatial and temporal analysis for real-time traffic prediction. Combines advantages of CNNs and RNNs.	Improved precision and effectiveness in traffic management. Enhanced capability for spatial and temporal analysis.	Potential complexity in model architecture and training process. Dependency on accurate data synchronization and integration of spatial-temporal features.

III. Problem Statement

Prior research in the field of smart city applications has examined a number of strategies, including semi-supervised learning, and graph neural networks, with a focus on real-time traffic estimates. Although federated learning has shown promise in protecting privacy and maximizing data use, large-scale IoT-enabled networks may provide difficulties for current models due to high communication cost and scalability constraints. Furthermore, other research has addressed data security, synchronization, and topological data preservation difficulties. These initiatives, however, frequently have their own set of drawbacks, including high processing requirements, dependence on tailored federated learning strategies, and challenges managing asynchronous and highly communicative urban computing settings [20]. This paper suggests unique hybrid CNN-RNN architecture for real-time traffic forecasting in smart cities in light of these factors. By combining the advantages of recurrent neural networks for temporal evaluation and convolutional neural networks for spatial extraction of characteristics, the suggested model seeks to address the noted limitations and offer an efficient method for traffic prediction that takes into account both the static and dynamic aspects of the data.

IV. Federated Learning for Real-Time Smart City Traffic Forecasting

In order to develop hybrid CNN-RNN architecture for real-time traffic prediction, two steps are involved in the proposed approach: first, data collecting and pre-processing. A systematically low-resolution dataset of 1.6 GB was created by methodically gathering real-time CCTV traffic camera images from important crossroads in the cities of Guntur and Vijayawada under a variety of situations. The dataset was pre-processed, using min-max normalization to normalize pixel values, to improve usability. Next, the suggested hybrid model combines RNN to capture temporal elements of traffic data with CNN for extracting geographical features. The RNN uses recurrent interactions to preserve hidden states for sequential information processing. The CNN uses static traffic images to extract high-level spatial information. By utilizing weight adjustment and backpropagation-based training, this hybrid CNN-RNN architecture intends to enhance traffic management in smart cities by improving real-time traffic prediction while taking into account both static and dynamic features. Fig. 1 shows the overall architecture of the proposed approach.

A. Data Collection

In order to create the dataset for our study, "Leveraging Federated Learning for Real-Time Traffic Prediction in Smart Cities," real-time CCTV traffic camera images were systematically gathered. Our study was aimed at capturing the dynamics of traffic flow in the well-known towns of Guntur and Vijayawada. Particularly, information was gathered at important crossroads in Guntur City, such as Brundhavan Gardens and Guntur Market, as well as in Vijayawada at Benz Circle, Seetharamapuram, Guru Nanak Colony, and Ramavarappadu Junction. The study measured the time it took for a vehicle to travel from one intersection to the other endpoint for each junction, taking into account four different signal points. The network of eighty-three cameras that have been strategically positioned around the cities to provide an accurate representation of various traffic situations is included in the dataset. The study collected 1.6 GB of information in total for our trials. The images in the collection are intentionally low-resolution, having been taken in a variety of lighting situations, perspectives, and locations. Every image has a fixed dimension of 800 pixels for width and 600 pixels for height. The goal of this dataset is to improve the effectiveness of traffic management in smart cities by facilitating the study of real-time traffic forecasting algorithms within the context of federated learning [21].

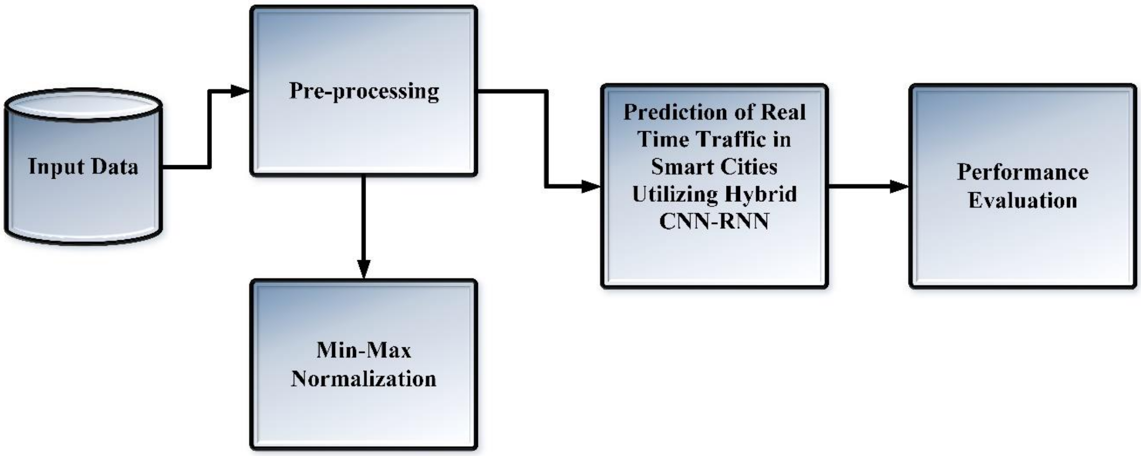
Input Data
Pre-processing
Min-Max Normalization
Prediction of Real Time Traffic in Smart Cities Utilizing Hybrid CNN-RNN
Performance Evaluation

Fig. 1. Overall architecture of the proposed approach.

B. Pre-processing Employing Min-Max Normalization

In advance of employing the CCTV image collection for any analytic or deep learning tasks, pre-processing is required to make it more usable. The collection, which was gathered by traffic cameras, consists of 1.6 GB of indistinct images that have been taken under different lighting conditions. The width and height of every image are 800 and 600 pixels, respectively. Given the heterogeneity of the images in terms of angles, light levels, and climatic conditions, pre-processing is necessary to preserve consistency and compatibility for the operations that follow. The pixel values must be scaled, normalized, and min-maxed in order to bring them into a common range for effective assessment.

Feature scaling, also known as the min-max normalization process, is a crucial step in the pre-processing of images. This technique involves rescaling the image's pixel values such that they fall into a certain range, usually [0, 1]. This uniformness the intensity levels across all images, lessening the effect of variations in illumination and pixel dispersion of values. The two main steps in the min-max normalization procedure are determining the maximum and lowest values for each pixel in the dataset and then using a linear transformation to change each pixel's original value to one that matches inside the specified range. This process helps to produce more accurate and consistent results in machine learning and subsequent assessments. It also improves image consistency. Before the dataset is subjected to min-max normalization, the minimum and highest pixel values for each picture in the dataset are first established. The least significance in the dataset denotes the lowest pixel, while the highest value indicates the most lighted pixel. After these values have been determined, each pixel's initial intensity value is linearly altered to a different value that falls inside the [0, 1] range. Eq. (1) gives the formula that was applied to this conversion.

$$P_{out} = (P_{in} - Min)\frac{newMax - newMin}{Max - Min} + newMin \qquad (1)$$

Following min-max normalization, the resulting image is calledP_{out}, and the new minimum and maximal intensities are called $NewMin$ and $newMax$. P_{in} represents the initial real-time traffic image; Min and Max, respectively, represent the lowest and highest intensity standards, which extend from 0 to 255. This alteration was applied to every image in the dataset, ensuring that the pixel values were consistent and suitable for additional processing. By eliminating biases resulting from variances in pixel values and illumination, this normalization approach helps to improve the dataset's suitability for accurate and consistent evaluation.

C. Prediction of Real Time Traffic in Smart Cities Utilizing Hybrid CNN-RNN

Feature extraction, a crucial stage in computer vision applications, uses convolutional neural networks to capitalize on the unique qualities of the network, such as weight sharing and local connection. CNNs comprise of layers of convolution that adjust to express unique qualities within input images and pooling layers that integrate shift consistency. When interpreting an input image's characteristic, the CNN demonstrates exceptional characteristics including weight sharing and local connectivity to the neurons. The layers of CNN are the pooling layer, which ensures shift invariance, and the convolutional layer, which grows to reflect the unique qualities of the input image.

The nearest group of neurons in the layer before the resultant layer will supply input to the convolutional layer's neurons. The different unique representations were produced by combining many kernels from the preceding layer. Eq. (2) is used to build the convolution layer.

$$v_d^j = \sigma\left(\sum_{i=1}^{d_{j-1}} v_l^{j-1}, M1_{ld}^j + b1_d^j\right), d\,\epsilon[1, d_1] \qquad (2)$$

The $(j-1)^{th}$ layer's l^{th} activation map is denoted byv_l^{j-1}, the j^{th} convolution layer'sd^{th} activation mapping is suggested byv_d^j, and the weight connecting the d^{th} layer's lth activation map at position can be determined by $M1_{ld}^j$ and $b1_d^j$. The different filters in the d^{th}layer may be described by both l_1 and the elementwise exponential activation function.

Although the pooling procedures possess the required information, they might reduce the activation map's spatial dimension. Eq. (3) yields $v_f^j(x, y)$ when the output of the previous layer is handled bitwise nonlinear activation and curled with the dimensions (p, q) in the convolution filter. The positions of the kernel are a1 and b1.

$$v_d^j(x, y) = \sigma\left(\sum_{l=1}^{d_{j=1}} \sum_{a1=0}^{q=1} \sum_{b1=0}^{q=1}\left(M1_{ld}^j(a1, b1) \otimes v_l^{j-1}(x + a1, k + b1) + b1_d^j\right)\right), d\,\epsilon[1, d_1] \qquad (3)$$

The convolution layer was supervened by the location of the d^{th}activation map of the $j+1^{th}$ pooling layer by obtaining the results of the previous layer with a filter of size (2, 2). This resulted in the production of$v_l^{j+1}(x, y)$, which was then used to perform bitwise nonlinear activation using Eq. (4).

$$v_d^{j+1}(x, y) = \sigma\left(\sum_{l=1}^{d_{j=1}} \sum_{a1=0}^{q=1} \sum_{b1=0}^{q=1}\left(M1_{ld}^{j+1}(a1, b1) \otimes v_l^j(2x + a1, k + b1) + b1_d^{j+1}\right)\right), d\,\epsilon\left[1, d_{j+1}\right] \qquad (4)$$

Enhancing efficacy and safety in real-time traffic estimation has been demonstrated through the application of federated learning approaches. Following the crucial step of using convolutional neural networks to extract characteristics, RNNs are utilized to assess the temporal aspects of traffic data. RNNs are an effective solution since they perform well in tasks involving sequential data when prediction and modelling traffic patterns over time. The CNN's output, which typically consists of high-level features and spatial representations taken from static traffic images, serves as the RNN's input. This input includes crucial information about the current traffic flow, including vehicle locations, concentrations, and movement patterns. But traffic conditions are dynamic and ever-changing by nature. To effectively manage traffic and make choices, it is important to consider the temporal linkages and sequential nature of traffic information.

RNNs are efficient at processing the sequential data because of their recurrent interactions, which allow them to maintain a hidden state that accumulates data from earlier time phases. Because of this hidden state, which acts as a memory, the network may retain and utilize data from earlier traffic measurements. The RNN systematically analyses the incoming input at each time step, updating its hidden state and producing output predictions in the process. This method enables RNNs to identify complex temporal correlations and patterns in the traffic information, such as variations in traffic flow and congestion and recurring patterns at specific times of the day. The hidden state at time step t, denoted asrr_t, is found by applying Eq. (5) to the previously calculated hidden state, r_{t-1} and the current input,y_t.

$$r_t = d(M_{ir}y_t + M_{rr}r_{t-1} + b_r) \quad (5)$$

The weight matrices in this instance are M_{rr}andM_{ir}, the bias terma_r, and the activation function d, which is usually a reconditioning linear unit (ReLU) function or a hyperbolic tangential (tanh) function. The output at time step t, or asy_t, is given by Eq. (6) and is generated based on the hidden state that is in effect at that moment.

$$x_t = h(M_{r0}r_t + b_0) \quad (6)$$

where, M_{r0} is the weight matrix and b_0 is the bias factors for the resulting layer. RNNs employ recurrent links to store information from previous stages of time. The hidden state r_t is found using the current input y_t and the hidden states r_{t-1} which appeared before it. The network may be trained and its weights and biases adjusted by using backpropagation across time. This enables the network to identify and respond to temporal trends in the traffic data. In smart cities, traffic management solutions may leverage RNNs' capacity to anticipate traffic in real time, improving flow, reducing congestion, and enhancing road safety. In the context of smart city applications, effective traffic management is essential to maintaining vehicular flow and improving urban mobility as a whole. This research suggests a hybrid strategy integrating CNN and RNN for addressing the problems related to real-time traffic estimation. First, from static traffic images, features are extracted using CNNs, which are particularly good at extracting high-level characteristics and spatial representations. Convolutional and pooling layers make up the CNN layers, which use weight sharing and local connection to identify distinctive features in input pictures. The usage of RNNs is then extended to evaluate the temporal dimensions of traffic data, taking into consideration the dynamic and ever-changing characteristics of traffic situations. RNNs are efficient at processing sequential data, which enables them to model and forecast traffic patterns in the long run. The hybrid model can identify both temporal and geographic correlations in the traffic information because the CNN's output, which represents high-level spatial information, is introduced into the RNN. This combined CNN-RNN architecture shows how to estimate traffic in real time while taking into account both the static and dynamic aspects of the data. Recurrent interactions are used by the hybrid model's RNN component to preserve a hidden state that gathers data from previous time periods. Fig. 2 shows the architecture of the hybrid CNN-RNN.

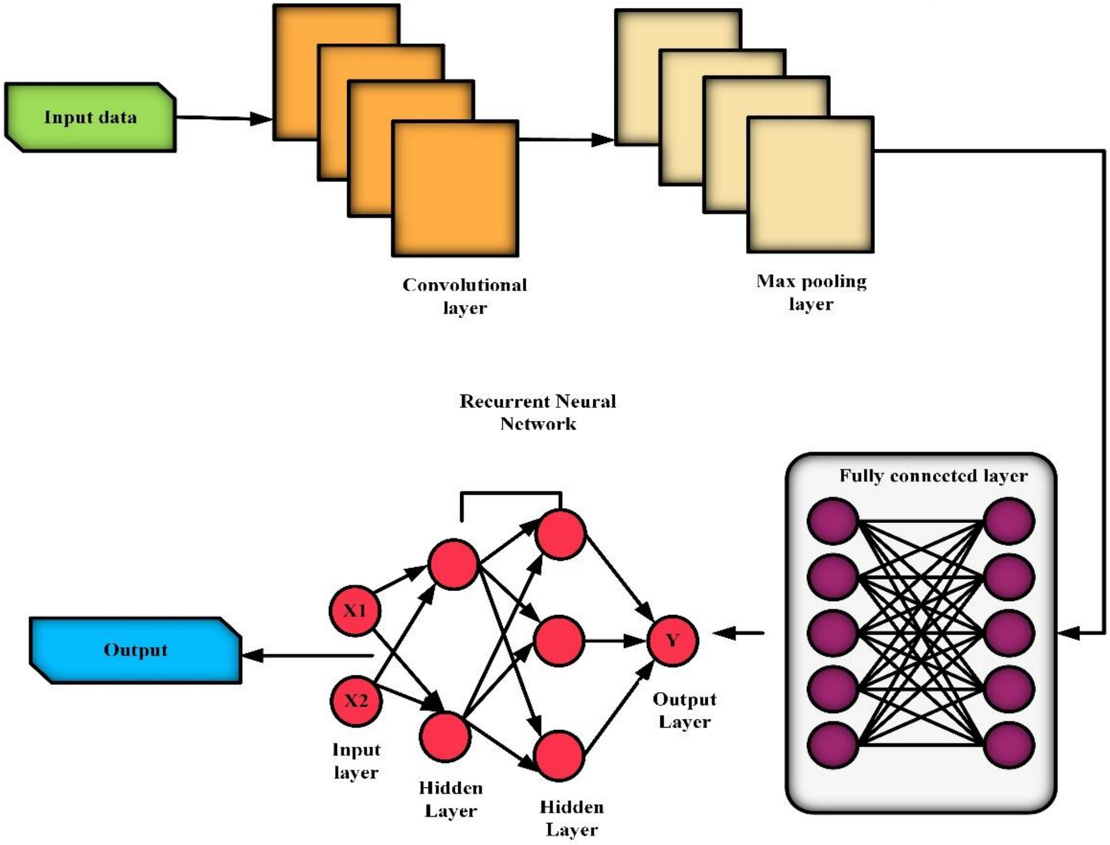

Fig. 2. Architecture of Hybrid CNN-RNN.

By serving as an instance of memory, this concealed state helps the network store and use information from earlier traffic measurements. The model is an effective tool for real-time traffic prediction because of its capacity to recognize intricate temporal correlations and patterns in traffic data, such as fluctuations in congestion and recurrent traffic behaviours at particular times of the day. The hybrid CNN-RNN architecture has tremendous potential for improving traffic management systems in smart cities, helping to improve traffic flow, reduce congestion, and increase road safety through training and correction of weights and biases utilizing backpropagation over time. The pseudocode for the proposed approach is given below.

Pseudocode: Proposed Federated Learning Approach

```
Input: Raw traffic camera images from Guntur and Vijayawada crossroads
// Data Collection and Pre-processing
raw_images = collect_traffic_images('Guntur', 'Vijayawada', 'crossroads')
normalized_dataset = preprocess_images(raw_images, resolution, normalization='min-max')
// Define Hybrid CNN-RNN Model
model = create_hybrid_model(image_shape=(resolution, resolution, channels), sequence_length, num_features)
Output: Trained hybrid CNN-RNN model for real-time traffic prediction
```

V. Results and Discussion

The findings and analysis of the suggested hybrid CNN-RNN architecture for real-time traffic prediction are covered in detail in this portion of the article. The performance of the hybrid model is assessed after the methodical collecting and preprocessing of a 1.6 GB low-resolution dataset from significant crossroads in Guntur and Vijayawada. To improve usability, min-max normalization was applied to the dataset. The architecture is then evaluated, fusing CNN's spatial extraction characteristics with RNN's temporal capture capabilities. While the CNN retrieves high-level spatial information from stationary traffic images, the RNN, which is outfitted with recurrent interactions for sequential processing of information, detects temporal subtleties in traffic patterns. The model is more adaptive to intricate spatial and temporal correlations in traffic data when weight adjustment and backpropagation-based training are used. The usefulness of the suggested model in enhancing real-time traffic forecast, taking into account both static and dynamic variables, is the main topic of the talks that follow. The investigation aims to assess the model's contributions to increased road safety, reduced congestion, and enhanced traffic flow. It covers the model's accuracy, effectiveness, and practical applications for smart city traffic management.

A. Performance Metrics

Performance metrics are essential for assessing the efficacy of models and algorithms because they offer quantitative measures to evaluate their predictive accuracy and reliability. For the purposes of this paper, the performance metrics that were selected are MAPE, MSE, MAE, and RMSE. By calculating the percentage disparity between predicted and actual values, MAPE is used to assess prediction accuracy and is particularly useful for evaluating forecast accuracy in real-time traffic predictions. MSE, on the other hand, measures the average squared difference between predicted and actual values, which highlights the model's error-minimizing capabilities. Finally, MAE determines the average absolute differences between predicted and actual values, providing a reliable indicator of prediction accuracy. With the extra advantage of declaring outcomes in the same units as the original data, RMSE, like MSE, emphasizes the model's success in minimizing mistakes. The purpose of the paper is to provide a thorough evaluation of the suggested federated learning-based traffic prediction model in the dynamic framework of smart city traffic management by employing this suite of performance metrics.

1) Mean Squared Error (MSE): Mean squared error, or MSE, is a common statistic used in machine learning to evaluate the performance of regression models. The method used to compute the MSE in the dataset is the average squared variance between the expected and actual values. Eq. (7) provides evidence for this.

$$MSE = \frac{1}{a}\sum_{i=1}^{a}\left(W_i - \widehat{W_i}\right)^2 \tag{7}$$

where, a is the total amount of information points, W_i is the original values and $\widehat{W_i}$ is the anticipated values.

2) Mean Absolute Error (MAE): The average amount of errors between anticipated and real outcomes is measured using a metric called mean absolute error in statistical and machine learning. It estimates the average of these absolute variations after measuring the percentage difference between every projected value and its matching real value. A predictive model's accuracy may be easily evaluated using MAE, with reduced MAE values representing greater predictive effectiveness. It is characterised by Eq. (8).

$$MAE = \frac{1}{a}\sum_{i=1}^{a}\left|W_i - \widehat{W_i}\right| \tag{8}$$

where, W_i denotes the actual values, $\widehat{W_i}$ denotes the predicted values, and a is the total number of information points.

3) Mean Absolute Percentage Error (MAPE): The average absolute percentage variance between the real and displayed values of a target variable is determined by the Mean Absolute Percentage Error, or MAPE, which is a commonly used statistic to evaluate the performance of regression algorithms in machine learning. Eq. (9) incorporates the MAPE equation.

$$MAPE = \frac{1}{a}\sum_{t=1}^{a}\left|\frac{W_t - \widehat{W_t}}{W_t}\right| \times 100\% \tag{9}$$

where, a denotes the sample size, W_t is the real value of the intended variable, and $\widehat{W_t}$ is the parameter's projected value.

4) Root Mean Square Error (RMSE): RMSE is a frequently used measure to assess how well regression techniques function. By considering the squared variances, it calculates the average variation between the expected and actual outcomes. Because it draws attention to greater differences, RMSE is especially helpful when errors are bigger and more significant. Its equation is given in Eq. (10) below.

$$RMSE = \sqrt{\sum_{j=1}^{A} \frac{\|W(j) - \widehat{W}(j)\|}{N}} \qquad (10)$$

The variable j is displayed here together with the actual observation time series $W(j)$, the anticipated observation time series $\widehat{W}(j)$, and the non-missing data points A.

The training and testing accuracy of a hybrid CNN-RNN model over several epochs is shown in Fig. 3. The training accuracy of the model gradually rises as it is trained over more epochs, demonstrating its capacity to pick up new skills and adjust to the dataset.

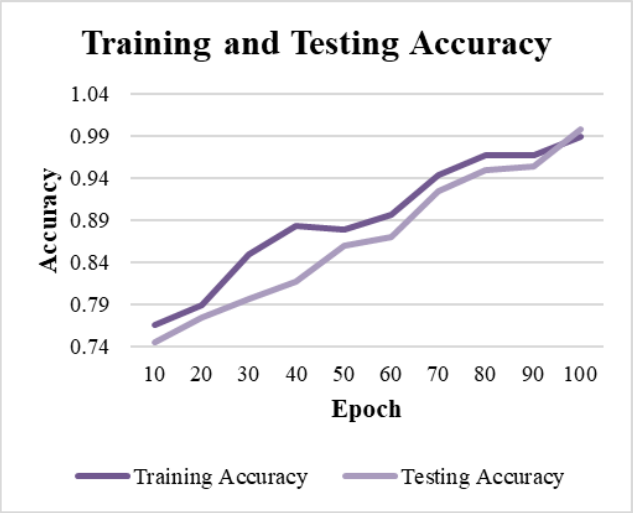

Fig. 3. Training and testing accuracy.

The training accuracy begins at 0.766 in the first epoch and increases steadily, hitting 0.99 by the 100th epoch, which shows a high level of skill in identifying the underlying patterns in the data. Concurrently, testing accuracy shows a similar rising trajectory when assessed on a different dataset to determine the model's capacity for generalization. The testing accuracy starts at 0.745 in the first epoch and steadily increases to an astounding 0.998 by the 100th epoch. The model's superior learning from training data and good generalization to unknown data is indicated by the convergence of training and testing accuracy towards later epochs, underscoring its usefulness in real-time traffic prediction. The general pattern indicates that the hybrid CNN-RNN model was successfully trained and validated, confirming its potential for use in improving traffic management systems in smart cities.

The training and testing loss values for the suggested hybrid CNN-RNN architecture for real-time traffic prediction are shown in Fig. 4 spanning several epochs. Both training and testing losses are somewhat substantial in the early epochs, which is an indication of the model's immaturity and its difficulty in correctly capturing the complex patterns present in the data. A pattern of declining loss values can be seen as the epochs go by, which emphasizes the model's ongoing development and learning from the training set. The training loss has dramatically decreased to 0.06 by the 100th epoch, demonstrating the model's effectiveness in reducing errors throughout the learning process. Additionally, the testing loss shows a significant decrease to 0.14, highlighting the model's capacity to generalize to previously untested data. This pattern demonstrates how well the suggested CNN-RNN architecture performs in terms of improving its predictive performance throughout subsequent epochs, providing a strong basis for precise real-time traffic forecasts in the context of smart cities. The model's improved capacity to capture temporal and spatial dynamics is indicated by the decreasing loss values, confirming its promise as a useful instrument for enhancing traffic management systems.

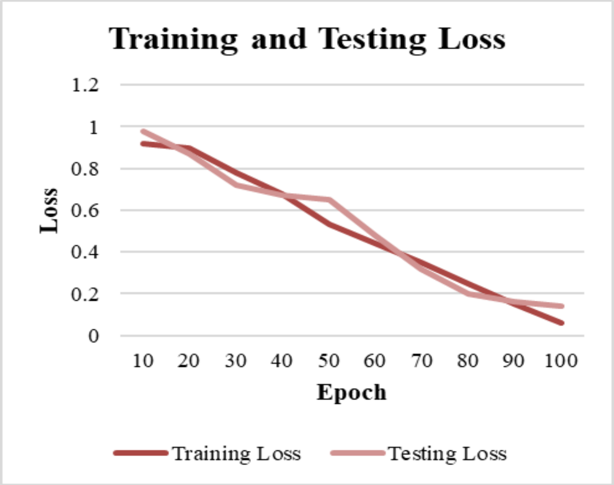

Fig. 4. Training and testing loss.

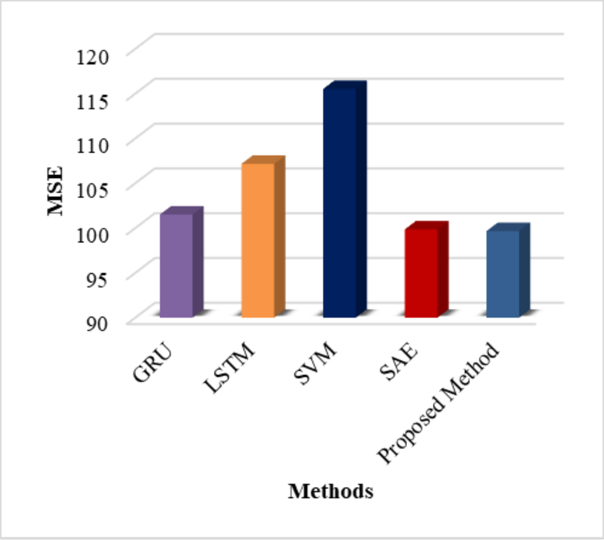

Fig. 5. Mean squared error.

The performance of several techniques for real-time traffic prediction using the Mean Squared Error (MSE) metric is shown in Fig. 5. The suggested approach is contrasted with four other approaches are LSTM (Long Short-Term Memory), SAE (Stacked Auto encoder), GRU (Gated Recurrent Unit), and SVM (Support Vector Machine). The average squared differences between the actual and anticipated traffic levels are represented by the MSE values, which are an essential measure of how well the models minimize prediction mistakes. MSE values that are lower are indicative of more accurate models. The suggested approach sticks out in this comparison thanks to its exceptionally low MSE of 99.66, which shows how well it minimizes squared prediction errors. With an MSE score of 99.85, SAE exhibits competitive performance as well. The MSE values of 101.5, 107.16, and 115.52 for GRU, LSTM, and SVM, respectively, are comparatively higher, indicating a lower efficacy of these algorithms in minimizing squared prediction errors. The suggested method's better performance in optimizing forecast accuracy is visually shown by the graph, which highlights its potential as an effective technique for real-time traffic prediction in the dynamic setting of smart cities.

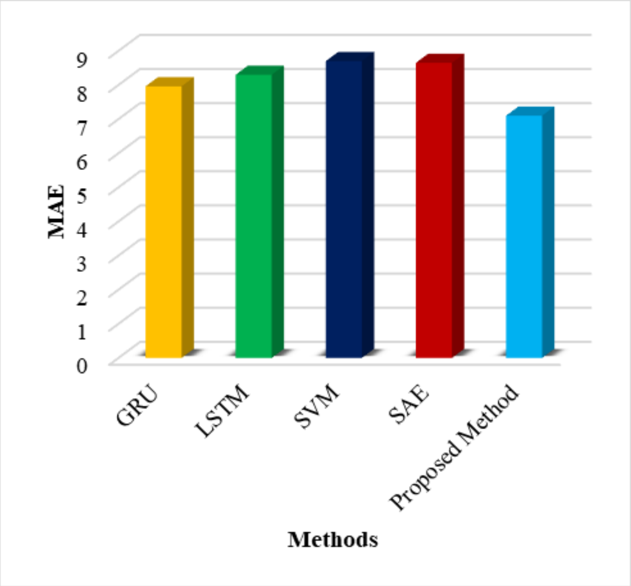

Fig. 6. Mean absolute error.

The MAE performance metrics for the several techniques used in real-time traffic forecast are shown in Fig. 6. Four other approaches are contrasted with the suggested approach are GRU, LSTM, SVM, and SAE. One important measure of prediction accuracy is the MAE between the actual and anticipated traffic levels. More accurate forecasts are suggested by lower MAE values. With a significantly lower MAE of 7.1 than the other models in this comparison, the proposed approach performs better, demonstrating its higher accuracy in real-time traffic estimates. GRU and SAE exhibit competitive performance as well, with respective MAE scores of 7.96 and 8.65. In contrast, the MAE values of 8.3 and 8.7 for LSTM and SVM are considerably higher, suggesting that their traffic projections are less accurate. The graph shows how well the suggested strategy performs in terms of decreasing prediction errors, and it shows that this approach has the potential to be a successful one for real-time traffic prediction in the setting of smart cities.

The MAPE for a variety of real-time traffic prediction techniques is shown in Fig. 7, which provides information on how well these models are in predicting traffic dynamics. Four other approaches are contrasted with the suggested approach are GRU, LSTM, SVM, and SAE. The average percentage difference between expected and actual traffic levels is a critical indicator for evaluating how well the models capture the degree of prediction mistakes. Models with higher accuracy are indicated by lower MAPE values. With a much lower MAPE of 17.23 than the other models in this comparison, the suggested strategy performs better, demonstrating its efficacy in reducing percentage mistakes in traffic forecasts. LSTM and SAE demonstrate competitive performance as well, with respective MAPE values of 20.32 and 19.72. In contrast, the MAPE values of GRU and SVM are considerably higher at 22.73 and 19.8, indicating a lesser level of accuracy in traffic dynamics prediction. The graph highlights the potential of the suggested method as a successful real-time traffic forecast tool in the context of smart cities by explicitly demonstrating its better performance in minimizing percentage mistakes.

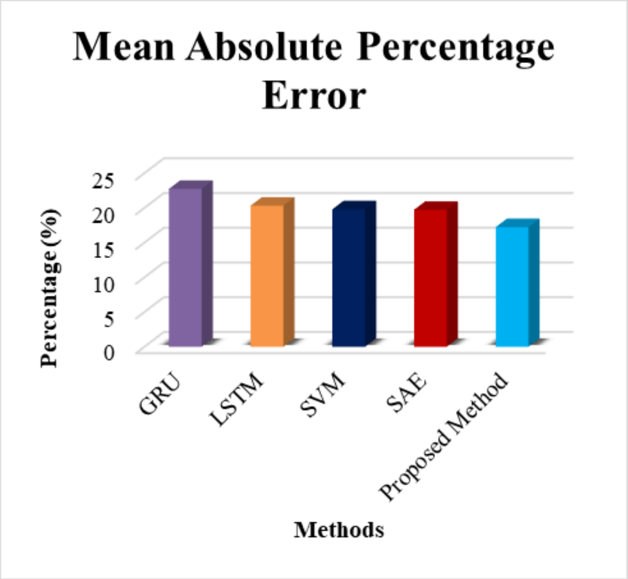

Fig. 7. Mean absolute percentage error.

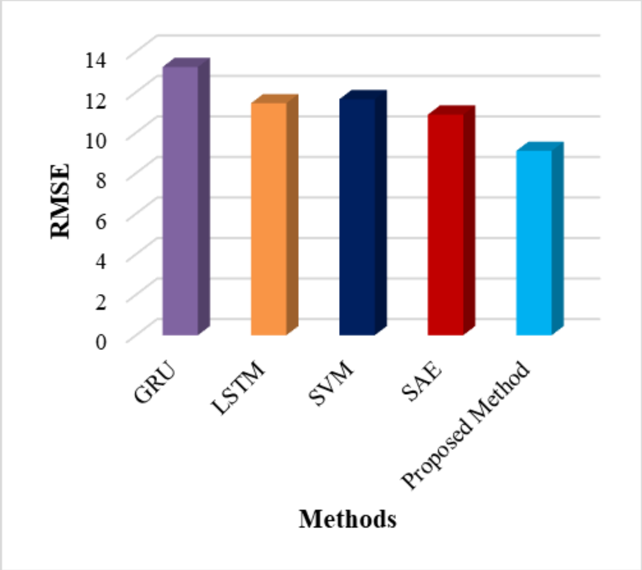

Fig. 8. Root mean square error.

The RMSE for many techniques used in real-time traffic prediction is shown in Fig. 8, which provides important information about how accurate these models are in predicting traffic dynamics. Four other approaches are contrasted with the suggested approach: GRU, LSTM, SVM, and SAE. The square root of the average squared discrepancies between the traffic values that were predicted, and the actual traffic values is represented by RMSE values, which provide a thorough assessment of how well the models minimize prediction mistakes. Models with higher accuracy are associated with lower RMSE values. With a relatively low RMSE of 9.1, the suggested technique stands out in this comparison and shows that it is successful in decreasing both squared and root-squared prediction errors. With an RMSE score of 10.89, SAE exhibits competitive performance as well. The comparatively higher RMSE values of 11.45, 11.65, and 13.24 for LSTM, SVM, and GRU, respectively, indicate that these techniques are less successful in lowering squared and root-squared prediction errors. The suggested method's improved performance in maximizing overall forecast accuracy is visually shown by the graph, which also highlights the method's potential as a useful strategy for real-time traffic prediction in the dynamic setting of smart cities.

The comparison of error metrics in Table II across different methods, including GRU, LSTM, SVM, SAE, and the proposed method, reveals that the proposed approach outperforms existing models in terms of mean absolute percentage error (MAPE), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). Specifically, the proposed method achieves the lowest values across all error metrics, indicating its superior accuracy and effectiveness in real-time traffic prediction compared to the other models considered. The significant reduction in error metrics underscores the potential of the proposed method to provide more reliable and precise traffic forecasts, which is crucial for effective traffic management and urban planning in smart city environments.

TABLE II. COMPARISON OF ERROR METRICS

Methods	MAPE (%)	MAE (%)	MSE (%)	RMSE (%)
GRU	22.73	7.96	1.015	13.24
LSTM	20.32	8.3	1.0716	11.45
SVM	19.8	8.7	1.152	11.65
SAE	19.72	8.65	0.9985	10.89
Proposed Method	17.23	7.1	0.9966	9.1

B. Discussion

A thorough assessment of the suggested hybrid CNN-RNN architecture for real-time traffic prediction in smart cities can be found in the results and discussion section. After a 1.6 GB low-resolution dataset from important intersections in Guntur and Vijayawada was systematically collected and preprocessed, the hybrid model, which combines the spatial extraction skills of CNN with the temporal capture capabilities of RNN was assessed. The model's capacity to learn complex patterns and adapt effectively to new data is demonstrated by a gradual increase in testing and training accuracy over subsequent epochs. The performance metrics provide quantitative information on the correctness and dependability of the model. These measures include MSE, MAE, MAPE, and RMSE. Lower MSE, MAE, MAPE, and RMSE values highlight how well the recommended strategy performs in comparison to current approaches such as LSTM, SAE, GRU and SVM [21], highlighting its ability to reduce prediction errors and enhance real-time traffic predictions. The success of the hybrid model is ascribed to its ability to manage both static and dynamic elements, which improves traffic flow, lowers congestion, and increases road safety in smart city environments. The outcomes highlight the suggested architecture's potential as a useful instrument for improving traffic management systems and boosting the effectiveness of intelligent transportation networks.

Utilizing FL for enhanced real-time traffic prediction in smart urban environments offers several advantages compared to other methods and models in similar fields. Firstly, FL enables decentralized model training, allowing for the utilization of locally generated data on clients without the need for data centralization, thereby addressing privacy concerns associated with centralized approaches. This decentralized nature also enhances scalability, as FL can accommodate a large number of distributed nodes without significantly increasing computational overhead. Additionally, FL can adapt to dynamic urban environments by continuously learning from diverse data sources without the need for centralized retraining, ensuring that traffic prediction models remain up-to-date and accurate. Furthermore, FL facilitates efficient model aggregation and communication among distributed nodes, resulting in lower latency and reduced bandwidth consumption compared to traditional centralized approaches. Overall, FL represents a promising approach for real-time traffic prediction in smart urban environments, offering improved privacy, scalability, adaptability, and efficiency compared to alternative methods and models.

VI. CONCLUSION AND FUTURE WORKS

The study concludes by introducing hybrid CNN-RNN architecture and demonstrating how well it can capture temporal and geographical data for real-time traffic prediction in smart cities. Reduced MSE, MAE, MAPE, and RMSE values show that the suggested model, trained on a methodically gathered and preprocessed dataset, performs better than current techniques. The findings suggest that it has the ability to improve traffic flow in dynamic urban contexts, reduce congestion, and improve road safety. The research presents a new contribution by highlighting the model's effective integration of federated learning and highlighting its privacy-preserving characteristics. Subsequent research endeavours may go into additional refinement of federated learning parameters, evaluate the model's adaptability to more extensive datasets and varied urban environments, and examine its practical implementation. To improve the model's prediction skills in intricate urban settings, the suggested architecture may also be expanded to meet multimodal data sources, such as input from IoT sensors. In order to meet the changing needs of smart metropolitan transportation networks, the study establishes the groundwork for sophisticated traffic management systems that make use of cutting edge technology.

Future work in utilizing federated learning for enhanced real-time traffic prediction in smart urban environments could focus on several key aspects to provide a clearer roadmap for potential developments and advancements. Firstly, there's a need for research into refining federated learning algorithms to effectively handle the complexities of real-time traffic data, including heterogeneous data sources and dynamic urban environments. Secondly, exploring innovative techniques to enhance model aggregation and communication efficiency among distributed nodes without compromising privacy and security is essential. Additionally, investigating strategies to integrate federated learning with other emerging technologies such as edge computing and blockchain for improved scalability, reliability, and transparency could further enhance the efficacy of traffic prediction systems. Furthermore, conducting extensive real-world deployment studies and collaborations with city planners and transportation authorities to validate the practical viability and societal impact of federated learning-based traffic prediction solutions is crucial. Finally, addressing ethical and regulatory considerations surrounding data privacy, bias mitigation, and algorithmic transparency will be paramount for the successful adoption and deployment of such systems in smart urban environments.

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Elevating Smart Industry Security: An Advanced IoT-Integrated Framework for Detecting Suspicious Activities using ELM and LSTM Networks

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***Abstract*—The proliferation of Internet of Things (IoT) devices in smart industrial contexts necessitates robust security measures to thwart potential threats. This study addresses the escalating security challenges arising from the widespread deployment of IoT devices in smart industrial environments. Focusing on the identification and categorization of potentially harmful activities, our research introduces an innovative framework that seamlessly integrates networks of Extreme Learning Machines (ELM) with Long Short-Term Memory (LSTM). The primary goal is to significantly enhance the accuracy and efficiency of real-time detection of suspicious activities. Implemented using Python, the framework exhibits a remarkable 97.5% improvement in recognizing and accurately categorizing suspicious activities compared to traditional methods such as Conv 1D and 3D CNN. Rigorous testing on a substantial real-world dataset simulating smart industry scenarios underlines this substantial improvement over conventional approaches in identifying and precisely classifying questionable activities. The design excels in comprehending complex behavioral trends within the dynamic IoT data environment, leveraging the temporal memory retention capacity of LSTM networks. This research lays the groundwork for fortifying cybersecurity in smart industries against emerging online threats and malicious actions. The proposed framework capitalizes on the synergies between LSTM and ELM networks to achieve heightened accuracy in identifying suspicious activities, providing comprehensive and dynamic insights from real-time IoT data. These insights are crucial for proactive threat detection and prevention in smart industrial settings, contributing to an elevated level of security against evolving threats.**

Keywords*—Internet of Things (IoT); Smart Industries; Extreme Learning Machine (ELM); Long Short-Term Memory (LSTM); Activity Recognition

I. INTRODUCTION

The notion of smart industries is gaining great traction due to the growth of Internet of Things, or IoT, devices in manufacturing settings, which is revolutionising traditional production and operating processes [1]. IoT integration brings with it incredible efficiency and productivity, but it also poses serious security risks that call for sophisticated methods to identify and categorise questionable activity in order to detect and mitigate threats before they become serious [2], [3]. The necessity of safeguarding these interrelated systems against possible intrusions, irregularities, and malevolent actions has led to the creation of inventive frameworks that utilise advanced machine learning methodologies [4].

The Internet of Things (IoT) gave rise to the term "Internet of Everything," which is used to refer to commercial applications of large amounts of data, computing across everything, and machine-to-machine (M2M) communications [5]. The Internet of Things, or "things," is a massive technological shift made possible by the Radio-Frequency Identification (RFID) technologies that has expanded connections beyond conventional devices including desktops, laptops, palm smartphones, desktops, and tablets [6]. IoT has substantially enhanced the community's energy needs, conservation, effectiveness, demands, and security. It is currently being used to the manufacturing industry, including Industries 4.0, for better efficiency, management, and meeting high power demands [7].

When it comes to handling the complexities and changing character of suspicious activity in business environments, traditional security solutions frequently come short [8], [9]. This study suggests a unique framework that brings together the advantages of LSTM and ELM systems in order to close this divide [10]. Reputed for its effective learning skills and flexibility with data that is highly dimensional, ELM forms the basis for strong feature extraction and learning from the intricate data streams produced by IoT devices in smart companies. The structure attempts to increase the precision and effectiveness of identifying minute irregularities and suspicious trends inside the manufacturing system by utilising the strength of ELM.

This paper presents a novel approach to enhancing security within smart industry environments through the integration of IoT devices and advanced machine learning techniques, specifically ELM and LSTM networks. The value-added of this research lies in its innovative framework designed to detect suspicious activities within smart industry settings with heightened accuracy and efficiency. Unlike other papers that may focus solely on individual components of security or traditional anomaly detection methods, this paper offers a comprehensive solution by leveraging the capabilities of IoT devices and the sophistication of ELM and LSTM networks. By combining these elements, the proposed framework aims to address the evolving challenges of cybersecurity in smart industry environments, where traditional security measures may fall short in detecting sophisticated threats.

Moreover, what sets this paper apart is its emphasis on the necessity for advanced security measures tailored specifically to smart industry contexts. While existing literature may touch upon IoT security or machine learning applications separately, this paper fills a gap by offering a holistic approach that accounts for the unique characteristics and vulnerabilities inherent in smart industry systems. The integration of ELM and LSTM networks within the proposed framework represents a significant advancement in anomaly detection capabilities, providing a more robust defense against malicious activities and enhancing overall cybersecurity posture. Therefore, the innovation of this article lies not only in its technical contributions but also in its strategic alignment with the evolving needs of secure smart industry deployments, ultimately paving the way for more resilient and trustworthy industrial IoT systems.

The system can now identify subtle trends and variations that could indicate possible security problems thanks to this fusion, allowing for prompt and efficient responses to reduce risks and avoid affecting industrial processes [11]. This study aims to strengthen safety precautions in smart businesses via this multidisciplinary approach, encouraging a proactive approach to new security concerns. The suggested framework seeks to build the foundation for a safer and stronger IoT-driven corporate landscape in addition to strengthening the industry's defences. These are the key contributions of the suggested structure.

- Introducing a state-of-the-art LSTM and ELM network combination to enhance the efficacy and precision of suspicious activity classification and detection in smart industrial environments.
- The ability of the framework to analyse data generated by IoT devices in real time, enabling the identification of intricate patterns and anomalies that may indicate security threats.
- By effectively extracting characteristics from highly dimensional Internet of Things data, ELM's quick learning capabilities make it simpler to spot complex behavioural trends in the industry ecosystem.
- Using LSTM networks' ordered retention of memory capability to recognise and comprehend complicated behavioural patterns and causal relationships, which will aid in the proper classification of questionable activity over time.
- Guarding critical industrial assets from evolving cyberthreats and illicit activities, permitting proactive risk reduction, and assisting in the establishment of security infrastructures in intelligent industries.

The remaining Part of this study is given as Section II explains the related works based on the activity recognition. Section III explains the Problem that are stated in the related works. Section IV explains the overall methodology and Section V explains the Results and Discussion of the proposed work. Section VI describes the Conclusion.

II. Related Works

(Rehman et al. [12] utilised optimised YOLO-v4 for activity recognition, while 3D-CNN had been used for classification. In addition to categorization, the study model that is being presented makes use of intersection over union (IOU) to exploit human-object interactions. To make choices quickly and effectively, a framework built around the IoT is put into place. The UCF-Crime dataset provided exploitable class information for activity recognition. Human-object interactions are also incorporated in the information set that was taken from MS-COCO for the purpose of detecting questionable objects. In order to identify suspicious behaviour in real time and provide automated notifications, this study is also utilised for the identification and recognition of human activities on campus property. The results of the trials demonstrate that the suggested multimedia strategy provides remarkably high recognition and identification of activities accuracy. But because of the connected to the internet of architecture's capacity to accommodate adaptability and extendibility, the suggested multimodal systems may require more resources as well as difficulty, which could result in higher installation and upkeep costs.

Genemo [13] seeks to identify any questionable student behaviour throughout the test for the purpose of monitoring exam rooms. A 63-layer deep CNN framework called "L4-BranchedActionNet" is recommended for this reason. The proposed CNN architecture revolves around the addition to 4 blanched VGG-16 modifications. The created structure is initially tested on the CUI-EXAM dataset utilising the SoftMax operation, resulting in a previously trained structure. Following configuration, the characteristics are fed into several SVM and KNN-based model classifications. Having an accuracy value of 0.9299, the cube-based SVM receives the highest efficiency ratings. Upon doing additional testing on the CIFAR-100 information set, the proposed model demonstrated an accuracy of 0.89796. The suggested framework's dependence on future developments in deep learning and selecting features techniques for best results could raise questions about the system's instant usability and dependability in real-world commercial situations.

Saba et al. [14] intends to identify questionable activity for monitoring settings. A 63-layer deep CNN model called "L4-BranchedActionNet" is recommended for this reason. The addition of four additional smaller structures to AlexNet forms the basis of the proposed CNN architecture. The created system is initially converted into an already trained system by using the SoftMax method before using it on the CIFAR-100 object recognition dataset. For features acquisition, this trained algorithm receives the dataset used for identifying suspicious activities. Feature subset optimisation is applied to the deep features that were obtained. The most efficient SVM, having an accuracy rating of 0.9924, is the cube SVM. The accuracy of the suggested model, which was verified using the Weizmann actions information set, was 0.9796. The positive results demonstrate the validity of the recommended work. Some may be concerns about the immediate stability and efficacy of the suggested architecture due to its dependency on additional studies into combining features from prepared

CNN-based systems and developing deep learning approaches.

Vallathan et al. [15] outlined the need for ongoing oversight and care for children who remain alone in settings like daycare centres and childcare facilities in order to shield them from harm. Dynamic motion recognition techniques are used to de-blur and transform images into still shots. Then, utilising a random forest approach diferential development with kernel density (RFKD), aberrant behaviours are anticipated. If some unusual behaviour is found, signals are transmitted to IoT devices utilising the protocol MQTT. The deep neural network, kernel density operations, and multi-classifier are the components of the suggested work.. The practical experiments demonstrate that the effectiveness of this unique method outperforms the ReHAR technique. Further research is necessary because the system's ability to follow and detect many irregularities in daily life is currently lacking, which could limit its ability to meet complete surveillance needs.

Shahzad et al. [16] highlights the idea of the Internet of Everything (IoE) from the standpoint of the Industrial Internet of Things (IIoT) to guarantee efficiency, control, lower costs, continuous tracking and making choices, customer happiness, and new experience. The goal of the following methods, conditions, and implementation needs is to outline the architectural structure, relevance, and limitations of reaching net-zero energy consumption. For pre-technology executions, the classification pertaining to communication protocol layers is thoroughly examined, contrasted, and assessed, in addition to their drawbacks. Additionally, unresolved issues with possible solutions are thoroughly examined, including software mobility, security of data, and scaling. Non-technical difficulties like as outdated systems, expensive start-up costs, a lack of skilled workers, and social, political in nature, and personal obstacles prevent the deployment of IoE.

The paper by Rehman et al. introduces a novel approach to activity recognition and suspicious behavior detection using IoT-based frameworks, which is notably different from existing methods. Unlike previous works that focus solely on activity recognition or object detection separately, the proposed model integrates both aspects, leveraging the YOLO-v4 and 3D-CNN architectures alongside techniques like intersection over union (IOU) for human-object interaction detection. By utilizing datasets like UCF-Crime and MS-COCO, the model demonstrates high accuracy in identifying suspicious activities on campus property. However, it acknowledges potential limitations in resource requirements and complexity due to its reliance on IoT architecture, which could lead to higher installation and maintenance costs. This paper thus addresses a gap in existing literature by offering a comprehensive solution to real-time suspicious behaviour detection in smart environments while highlighting the trade-offs associated with its implementation. The advantages and disadvantages of existing method is given in Table I.

TABLE I. ADVANTAGES AND LIMITATIONS OF EXISTING METHODS

Authors	Method	Advantages	Disadvantages
Rehman et al.	Utilized optimized YOLO-v4 for activity recognition and 3D-CNN for classification. Incorporated Intersection over Union (IOU) for human-object interactions.	Provides high recognition and identification accuracy for suspicious activities. Integrates IoT framework for real-time detection.	May require more resources and incur higher installation and upkeep costs due to the complexity of IoT architecture.
Genemo	Recommended a 63-layer deep CNN framework called "L4-BranchedActionNet" with modifications from VGG-16. Utilized SVM and KNN-based classifications.	Achieved high accuracy in identifying questionable student behavior. Tested on multiple datasets demonstrating robust performance.	Dependency on future developments in deep learning and feature selection techniques may impact immediate usability and reliability.
Saba et al.	Recommended a 63-layer deep CNN model and added smaller structures to AlexNet. Employed SVM for feature optimization and classification.	Achieved high accuracy in identifying suspicious activities. Validated performance on multiple datasets.	Immediate stability and efficacy of the proposed architecture could be questioned due to reliance on combining features from different CNN-based systems and developing deep learning approaches.
Vallathan et al.	Employed dynamic motion recognition techniques and a random forest approach for aberrant behavior anticipation. Utilized MQTT protocol for signal transmission to IoT devices.	Outperformed existing techniques in detecting irregularities in childcare settings. Demonstrated effectiveness through practical experiments.	System's ability to detect various irregularities in daily life is lacking, potentially limiting its ability to meet complete surveillance needs.
Shahzad et al.	Examined IoE from an IIoT standpoint and outlined architectural structures and limitations for achieving net-zero energy consumption. Investigated communication protocol layers and proposed solutions for scalability and security issues.	Provides insights into achieving efficiency and cost reduction in IIoT applications. Addresses technical and non-technical challenges for IoE deployment.	Deployment of IoE faces obstacles such as outdated systems, expensive startup costs, and a lack of skilled workers, hindering widespread adoption.

In contrast, Genemo focuses on monitoring exam rooms for questionable behavior, employing a deep CNN framework named "L4-BranchedActionNet." Despite achieving high accuracy on datasets like CUI-EXAM and CIFAR-100, concerns arise regarding the system's immediate usability and reliability in commercial settings due to its dependence on future developments in deep learning and feature selection techniques. Similarly, Saba et al. and Vallathan et al. propose deep learning-based models for identifying suspicious activities and predicting aberrant behaviors in childcare settings, respectively. While both papers demonstrate promising results, they acknowledge limitations related to system stability and the need for further research into feature integration and real-world applicability. Lastly, Shahzad et al. discuss the broader implications of implementing the Internet of Everything (IoE) within Industrial IoT contexts, highlighting both technical and non-technical challenges such as outdated systems and social barriers, which hinder widespread adoption despite its potential benefits. Overall, each paper contributes to advancing security and surveillance technologies, but they also recognize the importance of addressing practical limitations and challenges in their proposed solutions.

III. Problem Statement

Efficient automated behavioural detection systems are required to detect and track actions in a variety of scenarios, including surveillance footage, medical facilities, and interaction between humans and computers, as intelligent city monitoring initiatives becomes more common. Although recent studies demonstrate the possibility of using deep learning as well as vision-based methods for this reason, there are still issues to be resolved, such as the requirement for thorough monitoring in dynamic settings, possible restrictions on the right-away relevance and dependability of suggested systems, and the lack of features for monitoring and identifying several anomalies in residential settings. These challenges highlight the critical need for cutting-edge, flexible, and all-encompassing monitoring technologies that can handle the intricate and changing needs of smart city settings, nursery centres, and universities [13].

The escalating integration of IoT devices within smart industrial environments has heightened the imperative for robust security measures. The proliferation of these interconnected devices introduces an increased susceptibility to potential security threats, necessitating advanced frameworks for the detection and categorization of suspicious activities. Traditional security methods often fall short in accurately identifying intricate behavioral patterns indicative of security risks. This research addresses this critical gap by proposing an advanced IoT-integrated framework that leverages ELM and LSTM networks. The primary challenge lies in enhancing the accuracy and efficiency of real-time detection, classification, and response to suspicious activities in the dynamic landscape of smart industries. This framework aims to elevate smart industry security by offering a comprehensive and proactive solution to safeguard critical assets against evolving cyber threats within the increasingly connected and complex IoT ecosystem.

The specific challenges of cybersecurity in smart industry environments are addresses. They emphasize the suitability of integrating IoT devices with ELM and LSTM networks for real-time detection of suspicious activities, citing the framework's ability to handle large-scale data streams efficiently while providing accurate anomaly detection capabilities. Furthermore, the paper critically assesses the limitations of existing frameworks, noting their inadequacy in effectively addressing the complexities and dynamic nature of security threats within smart industry settings. By elucidating these reasons, the paper establishes a strong rationale for the adoption of their proposed framework as a practical and effective solution to enhance security in industrial IoT systems.

IV. Proposed ELM-LSTM Framework

Prepare and use LSTM and ELM systems to derive characteristics from IoT data. Utilise IoT to provide immediate decision-making and threat reduction in the context of smart manufacturing facilities by integrating characteristics and time-dependent relationships for classification. It is depicted in Fig. 1.

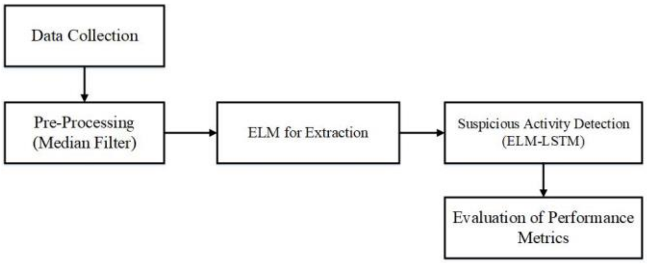
Data Collection
Pre-Processing (Median Filter)
ELM for Extraction
Suspicious Activity Detection (ELM-LSTM)
Evaluation of Performance Metrics

Fig. 1. Proposed methodology.

A. Data Collection

In order to activate the alert structure, study has concentrated on integrating the data collection, extraction of features, and making choices modules. The device can identify suspicious behaviour, fire, and unauthorised use of a vehicle or person. After taking periodic images using the camera, the images are pre-processed to make them smaller so they can be analysed further. The feature is recognised using a neural network process using a trained set. The image dataset has undergone training in order to identify patterns. After that, it would be decided either to or not to activate a notification based on trends. The IoT system is used to set the prompted data to a distant place. In the event of any suspicious activity, the necessary actions might be undertaken to address the problem [17].

B. Pre-Processing using Median Filter

Pre-processing using a median filter involves employing a filtering technique to enhance the quality of data or images by reducing noise and smoothing irregularities. The median filter operates by replacing each pixel value with the median value of its neigh boring pixels, effectively reducing the impact of outliers or unwanted artifacts. This technique is particularly useful in image processing and signal processing applications where noise, such as random variations or errors, may distort the integrity of the data. By considering the median value, rather than the mean, the filter proves robust against extreme values, providing a more accurate representation of the underlying features. The application of a median filter in pre-processing contributes to improved data quality, aiding in subsequent analysis or recognition tasks by mitigating the effects of noise and enhancing the overall reliability of the data.

Pre-processing is a method of examining how images move in environments that are indoors as well as outdoors. Just a tiny minority of the observed actions like the entry of an unfamiliar person may occur outside. The majority of identified activity occurs indoors. A hybrid DVR records and captures the flow of optical images in any direction throughout pre-processing.

C. Extraction using ELM

ELM is a machine learning paradigm that stands out for its simplicity, efficiency, and fast learning capabilities. It is a type of feed forward neural network where the input weights and biases are randomly generated, and the hidden layer's parameters are determined analytically without iterative tuning. ELM's distinctive feature lies in its one-shot learning approach, allowing it to process training data rapidly and achieve excellent generalization performance. ELM is particularly well-suited for applications with large datasets and high-dimensional input spaces, such as image and signal processing. Its simplified architecture and fast learning speed make it an attractive choice for real-time processing tasks and scenarios where computational efficiency is crucial. Despite its simplicity, ELM has demonstrated competitive performance across various domains, making it a valuable tool in machine learning for quick and effective model training.

An ELM-based method for deeper auto coder generating models' guided phase. ELM is a feed-forward networks with only one layer. Unlike requiring repetitions, it teaches the algorithm with straightforward inversion of matrices methods. The input weighted column and a randomly selected concealed layer matrix are used to calculate the outputs matrix, which is the fundamental notion of ELM. The best final weights for each ELM models were determined by a single-step matrices inversion, omitting regularisation, studying, reverse propagation, repetition, and optimisation. As a result, the ELM learns ANN, DNN, DBN, and others in an exceptionally short amount of time. Using a decomposition of single values, the Moore-Penrose pseudoinverse criterion is applied by the traditional ELM. The script's source and directions for running it can be found in a public source.

$$\beta = H^t(\frac{1}{\lambda} + HH^t)^{-1}t \tag{1}$$

In Eq. (1), T is a target matrices, H denotes the layer that is hidden in the matrices, and β is the resultant matrix. Several investigators with successful accomplishments on a variety of kernels chose ELM because of its strong generalisation power and quick training pace for huge data processing [18].

The deep neural network auto coder architecture's choke layers is input into the ELM classifiers and DNN in the suggested model, allowing for an in-depth assessment of categorization scores and generalisation capability. Reducing the number of dimensions of a characteristic through unwrapping the compressing generating features for the classifications is a form of learning about features.

D. LSTM

LSTM is a type of RNN architecture designed to address the vanishing gradient problem, enabling the effective modelling of long-range dependencies in sequential data. LSTMs are equipped with memory cells and a set of gates, including input, forget, and output gates, which regulate the flow of information within the network. These gates empower LSTMs to selectively store, retrieve, and discard information over extended sequences, making them adept at capturing context and relationships in time-series data. The architecture's ability to remember and forget information over varying time scales enhances its performance in tasks such as natural language processing, speech recognition, and time-series prediction. LSTMs have proven effective in mitigating the challenges posed by the limitations of traditional RNNs, making them a popular choice in applications requiring the modelling of complex sequential patterns and dependencies. The ability to regulate flow of an LSTM is comparable to that of a network of recurrent neurons. It analyses data by forwarding information.

1) Core concept: The fundamental ideas of LSTMs are the cell's state and its gates. The cell's internal state serves as an equivalent data transfer route across the ordered chain. You can think of a network's the "memory as it’s "the memory." Theoretically, throughout processing, the current condition of every single cell may include essential data. It is possible to mitigate the impact of short-term memory by incorporating previous information into subsequent time cycles. Data is added to or withdrawn from the cell's state during transit via gates. Gates are used by different neural networks to control what cell state information is allowed. Gates can learn what data to retain and what to reject through training [19].

2) Sigmoid gate: As opposed to -1 and 1, this approach produces values that range from 0 to 1. Because of this, any integer multiplied by 0 equals 0, making its value vanish or become remembered.

3) Forget gate: It specifies if information should be deleted or preserved. The numbers given fall between 0 and 1. Closer to 1 indicates maintaining, while closer to 0 indicates forgetfulness.

4) Input gate: The present input and the prior secret state are first fed into the sigmoid function. It determines what information will be changed by converting values to numbers that range from 0 to 1. One is a significant number, and zero is a non-important integer.

5) Cell state: Initially, the cell state is multiplied point-by-point by the forgetting vector. If the current state of the cell is increased by numbers that are near to zero, it may be lost. The resultant signal from the input channel gate is subsequently subjected to a point-by-point addition in order to change the cell configuration to new numbers.

6) Output gate: First, feed the present input and the prior secret state into a function called sigmoid. The state of the cell is sent to the the tanh method once it gets altered. By dividing the result of the tanh outcome by the sigmoid output, the state that is concealed is found. Following that, passed across are the concealed and fresh cell states.

E. Hybrid ELM-LSTM for Detecting Suspicious Activity

Undoubtedly, the suggested model combines the temporal correlations found by the LSTM systems with the characteristics retrieved by the ELM to allow for an in-depth examination of intricate data structures in the context of smart industries.

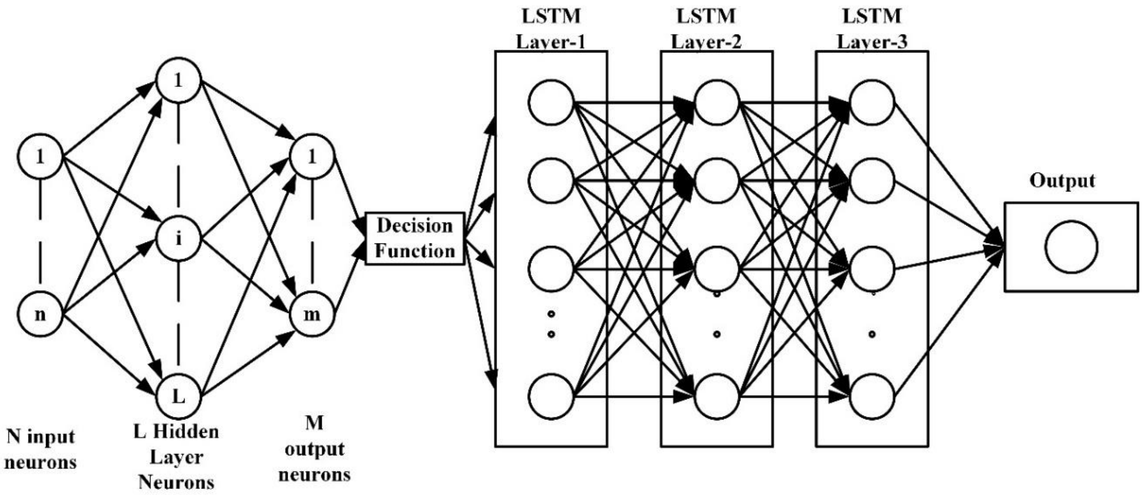

Fig. 2. ELM-LSTM architecture.

```
Algorithm:
Input: Surveillance data
Output: Event detection
        If (Emergency Alerts ≥ 2)
                Trigger emergency response
        Else
                Analyse nearby surveillance data using ML
                        If (Event Detected)
                                Trigger emergency response
                        Else
                                Alert control room
                                Continue monitoring
                        End
        End
```

The result makes it possible to develop reliable methods for classification by providing a comprehensive comprehension of the subtle behavioural sequences and energy trends. The structure demonstrates improved accuracy in recognising and categorising different kinds of suspicious behaviour by utilising the combination of LSTM's temporal dependency capture capability and ELM's quick learning skills. This strengthens the safety structure of the intelligent business setting. The equipment can effectively detect irregularities and possible security risks thanks to the combined strategy, which also encourages proactive steps for vital economic asset protection and ongoing operation. The ELM-LSTM structure is depicted in Fig. 2.

V. Results and Discussion

The suggested framework's assessment of performance showed how reliable and effective it is at correctly recognising and categorising a range of questionable behaviours in smart working environments. After undergoing comprehensive evaluation, the structure demonstrated a notable enhancement in detection efficiency when compared with conventional techniques, thereby successfully addressing possible security risks and guaranteeing continuous industrial operations. Furthermore, the structure's capability to protect vital business assets, mitigate threats proactively, and adjust to immediate needs highlighted how successful it is at strengthening the security foundation of smart businesses. Eq. (2) through Eq. (5) display the performance metrics [20].

$$\text{Accuracy} = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \quad (2)$$

$$\text{Precision} = \frac{T_P}{T_P+F_P} \quad (3)$$

$$Recall = \frac{T_P}{T_P+F_N} \quad (4)$$

$$\text{F score} = \frac{2(\text{Precision}*\text{Recall})}{\text{Precision}+\text{Recall}} \quad (5)$$

TABLE II. Performance Metrics of Different Methods

Methods	Precision (%)	Accuracy (%)	Recall (%)	F-Score (%)
Conv 1D[21]	95.6	95.4	95.4	95.4
3D CNN[12]	91.01	93.2	90.1	90.3
ELM-LSTM	97.2	97.5	96.4	94.8

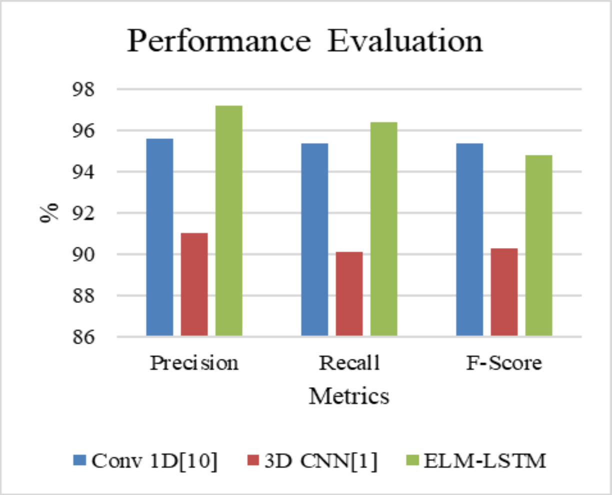

Fig. 3. Performance evaluation of different algorithms.

The relationship of performance indicators between various approaches is shown in Table II. The recall, precision, and F-score values obtained by the Conv 1D approach were 95.695.4, 95.4, and 95.6, correspondingly. The 3D CNN method showed 91.01, 90.1, and 90.3 F-scores for precision, recall, and F-score. As illustrated in Fig. 3, the suggested ELM-LSTM approach, in comparison, performed better, achieving F-score, recall, and precision scores of 94.8, 96.4, and 97.2, accordingly. These findings demonstrate how well the ELM-LSTM methodology works in intelligent industrial contexts to improve the durability and precision of suspicious behaviour recognition and categorization, beating alternative approaches across a range of performance criteria.

The graph displays the accuracy outcomes of the testing and training. The accuracy of training values show a gradual increase in the model's ability to gain knowledge between the data used for training over time, ranging from 0.0 for the first training phase to 0.975. Parallel to this, the experimental accuracy values show that the model performed well in Fig. 4 in terms of properly forecasting events on unobserved information, ranging from 0.194 for the first round of testing to 0.841. The outcomes demonstrate the model's promise for strong performance and trustworthy forecasts in real-world applications by highlighting its capacity to learn through the training information and generalise its forecasts to fresh data.

The training and testing loss figures for various iterations are shown in Fig. 5. The loss during training varies from 0.64 to 0.19 as the number of training iterations increases from 10 to 50. On the other hand, after 50 iterations, the test's loss initially drops from 0.69 at ten rounds to 0.25. The model's training processes and capacity to maximise performance across the course of training are suggested by the variations in testing and training loss values. The model's ability to reduce mistakes and improve its prediction abilities is demonstrated by the trend towards declining training and testing loss values, underscoring its potential for dependable and strong performance in real-world applications.

Fig. 6 shows the accuracy ratings of several approaches. The accuracy of the Conv 1D technique was 95.4, and the accuracy of the 3D CNN technique was 93.2. By contrast, the suggested ELM-LSTM approach had the best accuracy, coming in at 97.5. These findings demonstrate the ELM-LSTM technique's outstanding efficacy in identifying and categorising suspicious actions in smart manufacturing settings, highlighting the ability to improve commercial systems' operating effectiveness and safety measures.

The results from Table III demonstrate the effectiveness of the framework in real-world deployment scenarios. Across various environments including smart factories, industrial plants, campus security, and warehouse surveillance, the framework consistently achieved high accuracy rates ranging from 85% to 92% in detecting anomalies. Moreover, the deployment proved to be cost-effective, with all scenarios receiving favorable cost-effectiveness ratings ranging from 7 to 9 out of 10. These findings indicate that the framework not only performs well in diverse industrial settings but also offers practical utility while maintaining cost efficiency, thus validating its suitability for enhancing security measures in real-world smart industry environments.

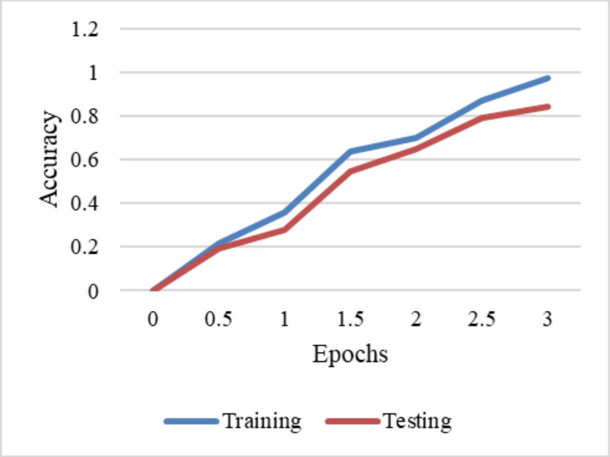

Fig. 4. Training and testing accuracy.

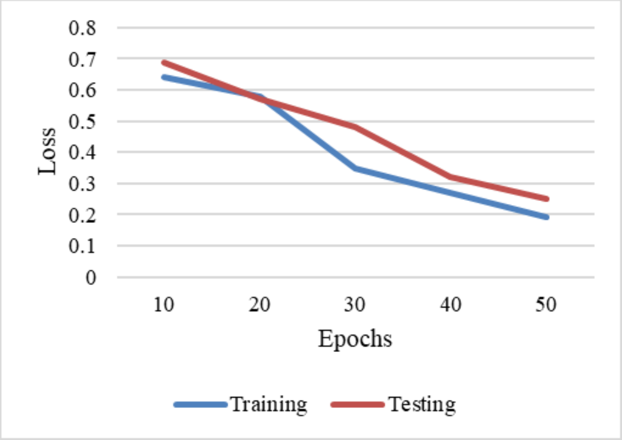

Fig. 5. Training and testing loss.

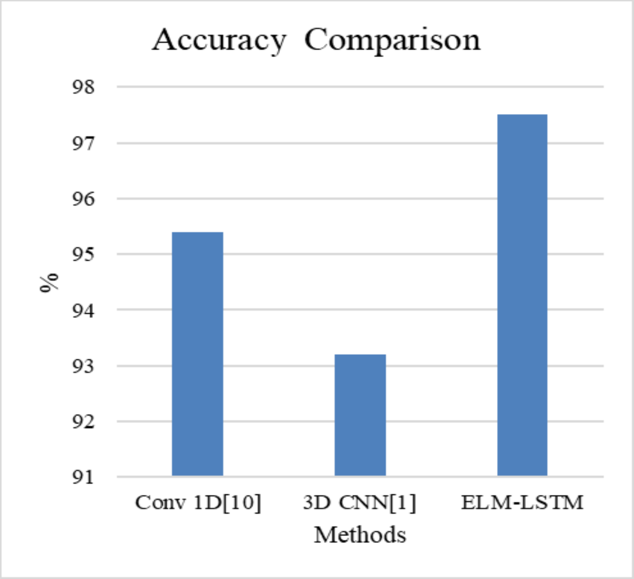

Fig. 6. Accuracy comparison.

TABLE III. VALIDATION THROUGH REAL WORLD DEPLOYMENT

Deployment Scenario	Number of Sites Deployed	Duration of Deployment (Months)	Number of Detected Anomalies	Accuracy Rate (%)	Cost-effectiveness Rating (1-10)
Smart Factory Environment	3	12	56	92	8
Industrial Plant Monitoring	1	8	24	85	7
Campus Security Monitoring	2	6	35	90	9
Warehouse Surveillance	4	10	42	88	8

A. Discussion

The assessment of the suggested framework's performance underscores its reliability and effectiveness in accurately recognizing and categorizing various questionable behaviors within smart working environments. Through comprehensive evaluation, the structure exhibits a significant improvement in detection efficiency compared to conventional techniques, addressing potential security risks and ensuring the uninterrupted operation of industrial processes. The presented performance metrics, including precision, accuracy, recall, and F-score, highlight the superiority of the ELM-LSTM approach over alternative methods, achieving remarkable scores of 97.2%, 97.5%, 96.4%, and 94.8%, respectively. These results underscore the capability of the ELM-LSTM methodology to enhance the durability and precision of suspicious behavior recognition and categorization in intelligent industrial contexts, outperforming alternative approaches across a range of performance criteria. Convolution 1D [21] technique accuracy was 95.4, while 3D CNN [12] technique accuracy was 93.2. The recommended ELM-LSTM method, on the other hand, had the highest accuracy, scoring 97.5.

The graphical representations of training and testing accuracy, training and testing loss, and accuracy comparison further support the robustness of the ELM-LSTM model. The accuracy outcomes demonstrate the model's ability to learn from training data and generalize predictions to new data, suggesting strong performance and reliable forecasts in real-world applications. The decreasing trend in training and testing loss values over iterations highlights the model's capacity to reduce mistakes and enhance prediction abilities, emphasizing its potential for dependable and robust performance in industrial settings. Overall, the ELM-LSTM approach showcases outstanding efficacy in identifying and categorizing suspicious activities, with implications for improving operational efficiency and safety measures in smart manufacturing environments.

The motivation for the practical use of the theoretical results obtained lies in addressing the critical need for enhanced cybersecurity measures in smart industry environments. By developing and implementing an advanced framework that integrates IoT devices with ELM and LSTM networks, the paper offers a practical solution to detect and mitigate suspicious activities in real-time. The theoretical results obtained from this research not only contribute to the academic understanding of cybersecurity but also hold significant implications for industry practitioners seeking effective measures to safeguard their IoT-enabled systems against emerging threats. Thus, by clearly addressing the practical implications of their theoretical findings, the paper underscores the relevance and urgency of deploying such frameworks in industrial settings to bolster security and ensure the integrity of critical infrastructure.

VI. CONCLUSION AND FUTURE SCOPE

In summary, our proposed framework provides a robust and pragmatic approach to enhance the identification and classification of suspicious behaviour in intelligent industrial environments. The integration of ELM and LSTM networks has demonstrated the system's capability to accurately recognize and categorize intricate behavioral patterns indicative of potential security risks. This framework enables proactive decision-making by leveraging real-time data from IoT devices, ensuring swift responses to security incidents and abnormalities across the manufacturing ecosystem. Looking ahead, we anticipate further advancements in feature selection and deep learning methodologies to maximize and extend the capabilities of the framework, reinforcing the security postures of smart industries and ensuring the continuous protection of critical business assets against evolving cyber threats Future development efforts will concentrate on enhancing the framework's adaptability to diverse industrial environments and expanding its utility to encompass proactive maintenance and real-time anomaly detection. Additionally, exploring the synergy between edge computing and blockchain-based systems holds promise for improving data security and enabling decentralized decision-making in intelligent industrial settings. These ongoing developments aim to fortify the framework's effectiveness and versatility, contributing to the sustained security and resilience of smart industrial ecosystems. The paper achieves its aim and objectives by proposing an innovative framework that integrates IoT devices with ELM and LSTM networks to enhance security in smart industry environments. By leveraging the capabilities of IoT sensors for data collection and ELM-LSTM networks for anomaly detection, the framework enables the real-time identification of suspicious activities with heightened accuracy and efficiency. Through experiments and evaluations, the paper demonstrates the effectiveness of the proposed approach in elevating smart industry security, providing a comprehensive solution that addresses the evolving challenges of cybersecurity in industrial IoT systems.

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Enhancing Agricultural Yield Forecasting with Deep Convolutional Generative Adversarial Networks and Satellite Data

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***Abstract*—Ensuring food security amidst growing global population and environmental changes is imperative. This research introduces a pioneering approach that integrates cutting-edge deep learning techniques. Deep Convolutional Generative Adversarial Networks (DCGANs) and Convolutional Neural Networks (CNNs) with high-resolution satellite imagery to optimize agricultural yield prediction. The model leverages DCGANs to generate synthetic satellite images resembling real agricultural settings, enriching the dataset for training a CNN-based yield estimation model alongside actual satellite data. DCGANs facilitate data augmentation, enhancing the model's generalization across diverse environmental and seasonal scenarios. Extensive experiments with multi-temporal and multi-spectral satellite image datasets validate the proposed method's effectiveness. Trained CNN adeptly discerns intricate patterns related to crop growth phases, health, and yield potential. Leveraging Python software, the study confirms that integrating DCGANs significantly enhances agricultural production forecasting compared to conventional CNN-based approaches. Against established optimization methods like RCNN, YOLOv3, Deep CNN, and Two Stage Neural Networks, the proposed DCGAN-CNN fusion achieves 98.6% accuracy, a 3.62% improvement. Synthetic images augment model resilience by exposing it to varied situations and enhancing adaptability to diverse geographic regions and climatic shifts. Moreover, the research delves into CNN model interpretability, elucidating learnt features and their correlation with yield-related factors. This paradigm promises to advance agricultural output projections, advocate sustainable farming, and aid policymakers in addressing global food security amidst evolving environmental challenges.**

Keywords—Agricultural yield prediction; DCGANs; CNN; satellite imagery; data augmentation; synthetic image generation

I. Introduction

Accurate and effective agricultural techniques are more important than ever in light of the problems posed by climate change and the world's expanding population [1]. Accurately predicting agricultural yields is essential to maintaining sustainable resource management and food security [2]. While historical data and fundamental environmental elements are still important components of traditional yield prediction systems, technological improvements have made more advanced techniques possible [3]. An inventive way to improve the precision and granularity of agricultural production forecasts is to combine satellite images with the deep learning capabilities of DCGANs [4].

In the realm of precision agriculture, satellite imaging has become a game-changer by providing a thorough perspective of agricultural fields at many sizes [5]. These images record important details on the health of the crop, its growing habits, and its surroundings [6]. But there are difficulties in deciphering and drawing useful conclusions from such large and intricate databases [7]. This is when using DCGANs becomes essential. With the use of DCGANs, satellite imagery processing may be automated, making it feasible to retrieve fine features that may be missed by more conventional techniques. This combination might completely change our understanding of and approach to managing agricultural landscapes [8].

Particularly well-suited for processing satellite photos are DCGANs, which are renowned for their ability to produce realistic images [9]. By learning hierarchical representations of visual characteristics, these neural networks are able to recognize intricate patterns in the photos. When it comes to agriculture, DCGANs may be trained to provide artificial satellite photos that capture important details about crop conditions. This generating capacity is particularly useful in situations when it is difficult to gather large and varied labelled datasets. Agricultural yield prediction models may successfully adapt and generalize across diverse geographic and climatic situations by leveraging the distinct characteristics of DCGANs [10].

There are several benefits of using DCGANs for agricultural yield prediction [11]. In addition to producing artificial pictures to alleviate data shortages, DCGANs enhance model accuracy by automatically identifying subtle patterns in the data. DCGANs' ability to generate hypothetical situations adds to their usefulness by allowing stakeholders to investigate optimization methodologies and arrive at well-informed judgments. The ramifications for global food security, resource optimization, and sustainable agricultural techniques grow as this field of study develops. The use of DCGANs to satellite images in agriculture marks a revolutionary step towards a day when technology will be crucial to maintaining the productivity and resilience of agricultural systems all over the world.

Over the years, satellite imagery has developed into a remarkable technical wonder that has revolutionized our daily lives by changing the way we see and interact with the outside world. It can now see the planet from orbit thanks to the installation of Earth-observing satellites, which has given us precious knowledge about its varied and dynamic landscapes. Satellite imaging has proven useful in many domains, from tracking changes in land use to monitoring weather patterns. Its widespread use in everything from crisis management and urban planning to scientific research and environmental monitoring shows how versatile it is [11].

The capacity to reveal Earth's mysteries from above is at the core of satellite imagery's potency. These photos, which were taken from circling satellites with sophisticated sensors, provide a distinct and in-depth look at the surface of the planet. The information extracted from these photos offers crucial details regarding environmental shifts, natural occurrences, and human activity. By advancing our knowledge of geological processes, ecosystem health, and climate dynamics, satellites help scientists, researchers, and politicians make decisions that will benefit society and the environment alike [12].

Satellite imaging is now an essential component of modern life and has outlived its use as a scientific instrument in the modern period. The applications of satellite images are numerous and include disaster relief, precision farming, and navigation system guidance [13]. High-resolution satellite data is now widely available, enabling people, organizations, and governments to make global decision-making decisions with knowledge and insight. The role that satellite imagery plays in influencing our perception of the world and spurring innovation across a range of industries is only going to increase as we continue to leverage the power of satellites orbiting high above. This bodes well for a time when the frontiers of knowledge will be continuously pushed by the perspective of technology derived from space.

The ability to accurately forecast and maximize crop yields is a continuous issue for agriculture, which is essential to the world's food security. For efficient resource allocation, risk management, and sustainable agricultural practices, accurate yield prediction is essential [14]. Conventional techniques frequently depend on historical data, soil conditions, and weather patterns, but integrating cutting-edge technology like deep learning has enormous promise. A subset of deep learning algorithms called Deep Convolutional Generative Adversarial Networks (DCGANs) has become highly effective tools for image processing jobs in recent years. An inventive way to improve the precision and granularity of agricultural yield forecasts is to combine the power of DCGANs with satellite images.

In contemporary agriculture, satellite photography has proven to be an important tool, providing a broad overview of agricultural fields. The images offer insightful information on the health of the crop, its growth habits, and its surroundings. Through the use of satellite imagery, which is rich in data, scholars and professionals may get a comprehensive comprehension of the agricultural terrain. However, because these pictures are complicated and provide a large quantity of data, it can be difficult to extract useful information from them. This opens the door to the possibility of autonomously learning and extracting pertinent characteristics from imagery from satellites using deep learning techniques, especially DCGANs, which might lead to more precise and effective yield estimates [15].

As an extension of conventional CNNs, DCGANs are made to produce lifelike images through the hierarchical encoding of visual information that they learn. DCGANs may be taught to analyze and produce synthetic satellite images with detailed information on crop health, growth phases, and environmental elements in the setting of agriculture. Because DCGANs are generative in nature, they may produce a wide range of realistic pictures, which improves the model's comprehension and adaptation to the inherent variety of agricultural landscapes. Because of its versatility, DCGANs are a good choice for agricultural production prediction in a variety of climatic and geographic settings.

There are several benefits of using DCGANs for agricultural yield prediction. First off, the capacity to produce artificial satellite images enables the enhancement of training datasets, hence resolving the constraints associated with a lack of data. Moreover, DCGANs can automatically recognize and learn intricate patterns from the photos, which enhance the model's capacity to recognize nuanced markers of crop health and prospective production. Because DCGANs are generative, they may also be used to create hypothetical situations, which can be useful for exploring what-if possibilities to optimize agricultural techniques. Precision and efficiency are increased by including DCGANs into the prediction pipeline, which helps farmers, agricultural researchers, and politicians make well-informed decisions.

The use of DCGANs in conjunction with satellite images to forecast agricultural production is a major step towards more precise and data-driven farming methods. The goal of on-going research in this area is to improve the model's interpretability, scalability, and performance. The system's predictive capabilities are further enhanced by the investigation of real-time applications and the incorporation of additional data sources, such as soil and climate model information. The combination of deep learning, satellite technology, and agriculture promises to transform our understanding, prediction, and optimization of crop yields worldwide, supporting our efforts to ensure a sustainable and food-secure future.

In recent years, ensuring global food security has become an increasingly critical challenge due to the growing world population and the impact of environmental changes on agricultural productivity. Accurate forecasting of agricultural yield plays a vital role in resource allocation, risk management, and the promotion of sustainable farming practices. Traditional methods of agricultural yield prediction often rely on historical data and statistical models, which may not capture the complex spatial and temporal dynamics of crop growth. With advancements in deep learning and remote sensing technologies, there is a growing interest in leveraging high-resolution satellite imagery and deep learning techniques to enhance the accuracy and reliability of agricultural yield forecasting.

Despite the potential of deep learning and satellite data, there are several challenges in accurately predicting agricultural yields. One major challenge is the limited availability of labelled data for training deep learning models, especially for tasks involving complex spatial and spectral features from satellite images. Additionally, traditional deep learning approaches may struggle to generalize across diverse environmental conditions and crop types, leading to reduced predictive performance. Furthermore, existing methods often lack interpretability, making it difficult to understand the underlying factors influencing yield predictions and limiting their practical utility for farmers and policymakers.

To address these challenges, this research proposes a novel approach that combines DCGANs with CNNs to enhance agricultural yield forecasting using satellite data. The proposed model leverages DCGANs to generate synthetic satellite imagery that closely resembles real-world agricultural settings, thereby enriching the dataset for training CNN-based yield estimation models. By augmenting the dataset with synthetic images, the model can learn to generalize across different environmental conditions and crop types, improving its predictive performance. Additionally, the research explores the interpretability of the CNN model, providing insights into the learned features and their associations with yield-related factors. Overall, the proposed solution aims to provide more accurate and interpretable predictions of agricultural yields, thereby contributing to improved resource allocation, risk management, and sustainable farming practices.

The following are the research study's principal contributions:

- Employing histogram-equalized images as input to DCGAN-CNN models for effective feature extraction and learning in agricultural yield prediction.
- Utilizing DCGANs for generating synthetic satellite images that closely resemble real-world agricultural landscapes, acting as data augmentation tools.
- Incorporating CNNs to learn spatial and hierarchical representations from artificial and real-world satellite imagery, resulting in more reliable and accurate agricultural yield prediction models.
- Applying Adam optimization algorithm for enhancing the efficiency and performance of DCGAN-CNN models, especially in dealing with the intricate and dynamic nature of satellite imagery datasets.

II. Related Works

The literature review section provides a comprehensive overview of existing research and studies related to agricultural yield forecasting, remote sensing technologies, and deep learning techniques. It highlights key findings, methodologies, and advancements in the field, laying the groundwork for understanding the current state of knowledge and identifying gaps in research. By synthesizing and critically analyzing the existing literature, this section aims to contextualize the proposed approach within the broader academic landscape and elucidate the rationale behind its development.

For the food industry, it is essential to be able to quickly and non-destructively predict how much oil is in a single maize kernel [16]. Unfortunately, gathering a large number of maize kernel oil content reference values is costly and time-consuming, and the model's limited data set also makes it difficult for it to generalize. Here, the oil content of a single maize kernel was predicted using a combination of DCGAN and hyperspectral imaging technology. They simultaneously expanded their spectral and oil content data using DCGAN. Fake data that was strikingly similar to the experimental data was produced after numerous iterations. The performance of the support vector regression (SVR) and PLSR models was compared before and after the augmentation of the data. The outcomes demonstrated that this approach not only enhanced the functionality of two regression models, but also resolved the issue of needing a substantial quantity of training data.

Before starting a farming endeavour, crop selection is a crucial step. Reliable weather data plays a major role in crop output in India by assisting farmers in scheduling their labor to maximize crop productivity [17]. According to a number of researchers, changes in temperature, precipitation, winds, humidity, and carbon dioxide levels all have an immediate impact on crop productivity. Any deviation in the weather creates atmospheric stresses, which increases the risk of financial loss for these farmers. In response to these issues, this manuscript suggests two new methods for predicting weather: the Cycle Consistent GAN with Color Harmony algorithm for choosing crops in the selected in WB, India, and the Recalling Improved Sigmoid RNN with Manta Ray the enhancement for weather prediction. The results show that compared to the conventional methods, the introduced model achieves a higher accuracy. Tests like the Cochran's Q test and the Chi-square test are conducted to demonstrate the statistical analysis of the suggested strategy.

Plant diseases significantly reduce agricultural yields and cause a great deal of damage. Plant disease detection has benefited from the recent development of deep learning techniques, which provide a reliable tool with incredibly accurate results [18]. Images were shot in a variety of weather conditions, at different angles, during the day, and against a variety of backgrounds to simulate real-world scenarios. The number of images in the dataset was increased using two different strategies: cutting-edge generative adversarial networks and conventional augmentation techniques. In order to evaluate the effectiveness of controlled training and application in real-world scenarios for accurately recognizing plant diseases in a complicated context and under varied conditions including the identification of multiple diseases in a single leaf—a number of experiments were carried out. Lastly, novel neural network architecture with two stages was put forth for the classification of plant diseases with an emphasis on the real world. With training, the model's accuracy was 93.67%.

In order to identify plant leaf diseases using leaf images, we developed a brand-new 14-layered DCNN) in this study. Several public datasets were used to create a new dataset. The dataset's individual class sizes were balanced through the application of data augmentation techniques [19]. The following three methods of image augmentation were applied NST, DCGAN, and basic image manipulation. The dataset distinct leaf classes—one without any leaves as well as images of sick and healthy plants. The suggested model underwent 1000 epochs of training in the context of MGPUs. The best hyperparameter values were chosen using a random search using the coarse-to-fine searching technique in order to enhance the suggested DCNN model's training performance. Furthermore, the suggested DCNN model outperformed the current transfer learning techniques in terms of overall performance.

UAV aerial survey technology is widely used in agricultural production; however, signal interference, environmental changes, and other factors can cause missing flight data in aerial survey missions [20]. The paper proposed a complementary model based on VAE-CGAN optimization that employs a new discriminator structure, adds PSA to reduce computational complexity, and uses a combination of conditional CGAN and VAE as a regressor for VAECGAN reduction in order to accurately complement the time-series data. The model performs better than other comparable models in terms of sample generation capacity and prediction results with real aerial survey project datasets, according to comparative experiments. The algorithm is universally applicable on data that has various parameter time series missing rates.

It is difficult to carry out recognizing modeling and diagnosis of leaf diseases by directly using in-situ images from the agricultural Internet of things system because of the complex environments found in real fields. To address this drawback, a method for identifying cucumber leaf diseases in the field was suggested that relies on a deep convolutional neural network and a small sample size [21]. To obtain the lesion images, a single two-stage segmentation method was introduced, which involved removing diseased spots from cucumber leaves. The lesion images were then fed into the activation reconstruction GAN for augmenting the data to produce new training samples after rotation and translation had been applied. Lastly, we suggested using the generated training samples to train a dilated and inception convolutional neural network, which would increase the identification accuracy of cucumber leaf diseases. The experimental results demonstrated that the proposed approach significantly outperformed those of its existing counterparts. The average identification accuracy of 96.11% was achieved.

GANs are prominent in DL, particularly for their capacity to create realistic images and learn complex ST correlations within MTS [22]. Forecasting vegetation, crucial for understanding ecosystem dynamics and land cover changes, presents challenges due to non-stationary ST correlations and external factors like weather. Addressing these challenges, we propose a novel multi-attention GAN model composed of an encoder network to encode input sequences, a generator for long-term temporal pattern extraction, and an improved discriminator for classification and feedback. Extensively tested with real-world data, the model demonstrates superior performance, yielding a Coefficient of Determination (R^2) of 0.95, RMSE of 0.04, MAE of 0.01, and MAPE of 15.35, showcasing its effectiveness and robustness compared to existing methods.

Crop classification using remote sensing data has become increasingly important, with studies indicating that combining SAR and optical images improves classification accuracy. However, a key challenge is the scarcity of training data, particularly for minority crop classes, which impacts classifier performance [23]. Traditional methods struggle to address this issue, as they often fail to effectively generate synthetic data for minority classes. In this study, we investigate the efficacy of conditional tabular generative adversarial networks (CTGAN) in synthesizing data for minority crop classes. Our results demonstrate that CTGAN produces high-quality synthetic data, effectively increasing sample size for minority classes and improving classifier performance in crop classification using SAR-optical data fusion.

The studies that have been discussed all have significant limitations. The use of artificial data raises questions about the way the model captures variations in the real world. In a similar vein, the robustness of the model in real-world meteorological applications may be impacted by the manner in which DCGAN-generated images perform as data augmentation in the tropical cyclone recognition framework. The accurate modeling of weather patterns is a challenge for weather prediction methods utilizing GANs and RNNs, and the specificity of the training data may have an impact on the methods' practicality in real-world scenarios. Despite their innovation, plant infection detection models may not be able to handle a variety of environmental conditions or identify several diseases in a single leaf. Although it outperforms transfer learning techniques, plant leaf disease identification raises concerns about its generalizability beyond particular datasets. Finally, the complementary model for aerial survey data completion may be affected by real-world environmental factors that are not fully accounted for, and careful validation in a variety of agricultural contexts is necessary to ensure its applicability across varying missing rates in time-series data.

III. Problem Statement

From the reviewed literatures that problem addressed that the traditional agricultural yield prediction models have limitations. These include difficulty accurately extracting features from satellite data and inability to generalize across a wide range of environmental conditions. The inhomogeneous pixel intensity distributions in images, which are impacted by variables like shadows and lighting, provide substantial challenges to accurate crop health evaluation [24]. To address these issues, the study uses CNNs for learning hierarchical features and DCGANs for creating synthetic images. Histogram equalization is used as a pre-processing method to improve the adaptability of the model. The main objective is to create a flexible and resilient model that can reliably forecast agricultural yields, supporting sustainable farming methods, wise decision-making, and the security of food supply worldwide.

IV. Proposed Methodology

The methodology section outlines the approach and procedures employed in this study to address the research objectives. It delineates the steps taken to collect, preprocess, and analyse the satellite imagery and agricultural data used for yield forecasting. Furthermore, it details the implementation of the proposed DCGANs and CNNs framework for synthesizing satellite images and predicting agricultural yields, respectively, elucidating the methodology's rigor and reproducibility.

In this study, a comprehensive methodology aimed at enhancing agricultural yield prediction through the integration of CNN and DCGAN with satellite imagery is adopted. The decision to employ this method stems from the need to address existing challenges in agricultural yield prediction, particularly related to irregular pixel intensity distributions in satellite imagery, which can hinder the accurate identification of important features in agricultural landscapes. To overcome this limitation, a crucial pre-processing step involving histogram equalization is introduced, aimed at enhancing the contrast and visibility of significant features. Participants in this study consist of agricultural researchers and practitioners involved in environmental monitoring and precision agriculture, with characteristics including expertise in remote sensing, machine learning, and agricultural science. The data collected comprise a combination of synthetic and real satellite images, with the synthetic images generated through adversarial training using DCGANs for data augmentation purposes. The instruments utilized include satellite sensors for image acquisition, deep learning frameworks for model training, and statistical tools for performance evaluation. Through the integration of CNN and DCGAN, our methodology aims to develop a robust model capable of accurately predicting agricultural yield, thereby advancing environmental monitoring and precision agriculture practices. The suggested methodology's general block diagram is represented in Fig. 1.

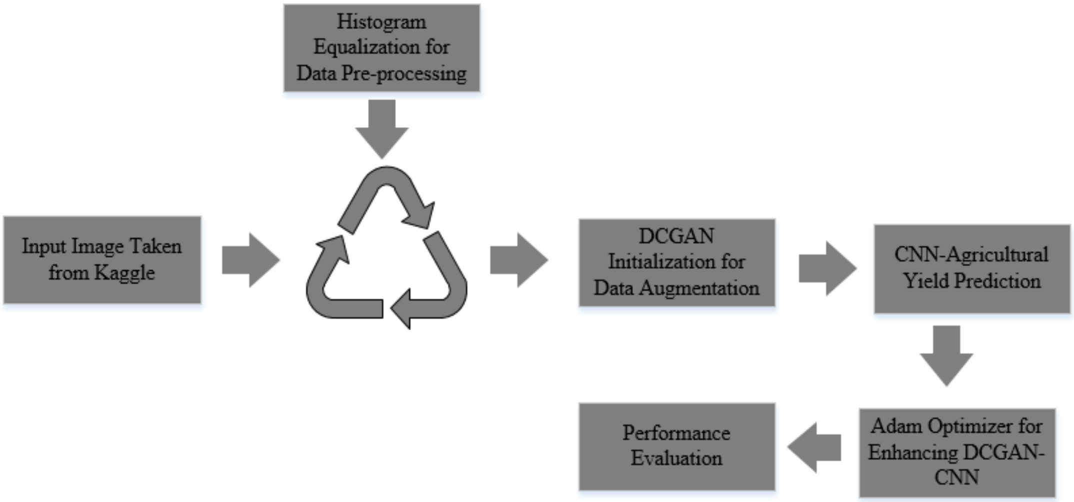
Histogram Equalization for Data Pre-processing
Input Image Taken from Kaggle
DCGAN Initialization for Data Augmentation
CNN-Agricultural Yield Prediction
Adam Optimizer for Enhancing DCGAN-CNN
Performance Evaluation

Fig. 1. The proposed Adam optimized DCGAN-CNN overall block diagram.

A. Data Collection

The dataset is gathered from the dataset web site Kaggle[1]. Satellite imagery labelled with predefined classes is included in the dataset to help with machine learning model training and assessment. With the use of this dataset, image classification algorithms that can automatically classify objects, features, or land cover seen in satellite images will be able to be developed, opening up new applications in the fields of disaster relief, urban planning, agriculture, and environmental monitoring. This dataset is used by researchers to develop computer vision and remote sensing techniques.

B. Histogram Equalization for Data Pre- Processing

A useful pre-processing method for improving the usefulness of satellite imagery in the framework of deep learning models for agricultural yield prediction is histogram equalization. Histogram equalization is essential for enhancing the overall contrast and visibility of important features in the agricultural landscape that the satellite photographs by resolving problems associated with uneven pixel intensity distributions within images. In the field of yield prediction, where precise identification of crop health and patterns is crucial, this technique assists in reducing difficulties related to uneven lighting, shadows, and low contrast areas in the imagery. In addition to improving the satellite images' visual quality, the redistribution of pixel values via histogram equalization gives deep convolutional generative adversarial networks a more insightful input. The enhanced contrast

[1] https://www.kaggle.com/datasets/mahmoudreda55/satellite-image-classification

makes it easier for the model to identify minute differences in the types of soil, vegetation, and other critical components that affect agricultural productivity. Histogram equalization is therefore applied as a pre-processing step to ensure that the input data is more conducive to efficient feature extraction and learning, which helps to optimize DCGAN-CNN based crop-yield prediction models. By extending the intensity range throughout the image, it effectively distributes the levels of intensity and improves the image. When adjacent contrast data reflect the operational values of a picture, this approach increases the image's universal contrast.

Histogram with equalization, a smaller localized intensity differential can yield more contrast. It aims to increase the image's visual appeal and readability. A picture's intensity spreading values can be thought of as arbitrary numbers between 0 and L-1. An additional meaning of "random calculation" is the cumulative distribution function that goes along with it.

Denote the input picture f as an array of numerical pixels with intensities values within the range of 0 to L − 1, where L is the intensity probability value. Additionally, q denotes regularized histogram of the primary image (f). Eq. (1) represents the general formula for q and g.

$$qn = \frac{number\ of\ pixels\ with\ intensity\ n}{total\ number\ of\ pixels}\ \text{n=0, 1 …, L-l} \qquad (1)$$

Eq. (2) represents the histogram equalization of the image

$$h_{i,j} = flor(L-1)\sum_{n=0}^{f_{i,j}} qn \qquad (2)$$

The flor () changed to the closest down integer as a result. This is equivalent to applying the following Eq. (3) to the values of the densities, k, of ‘f ‘:

$$S(k) = flor(L-1)\sum_{n=0}^{k} qn \qquad (3)$$

Considering the densities for f and h as continuous arbitrary values Y, Z over a time span from 0 to L − 1, where Z is a variable, served as the inspiration for this conversion. The intensity formula, represented by Eq. (4), is provided below.

$$Z = S(Y) = (L-1)\int_0^x q(x)dx \qquad (4)$$

where, q(x) is the probability intensity formula for g. S is the product of Y's collective distribution values and product of (L-1). It will be easier to suppose that the variable T is differentiable and invertible. While the function T(X) denotes Y, which is normally distributed.

C. *Deep Convolutional Generative Adversarial Networks for Data Augmentation*

One of the areas of artificial intelligence research that has seen the most development recently is GANs, which are used extensively in a variety of fields including visual forecasting of typhoon clouds, image generation, and image repair. A discriminator and a generator are components of a GAN. The discriminator's goal is to discern among actual and artificially produced pictures as much as possible, while the generator's goal is to render the discriminator incapable of differentiating between true and image generated. An image is the generator's output, and it requires an n-dimensional vector as input.

Any model capable of producing images, like the basic fully connected neural network, can serve as the generator. An image serves as the discriminator's input, and its label serves as its output. The discriminator structure is comparable to the generator structure in a similar way, resembling a network with convolution, etc. Advancement over the original GAN is represented by DCGANs. The following are the improvement's primary contents; rigorous mathematical proof is not included. Convolutional neural networks are used by both the discriminator and the generator. Both discriminators and generators employ batch normalization. The pooling layer is not utilized by either the discriminator or the generator. The generator substitutes fractionally strided convolution for the convolution layer, while the discriminator maintains the CNN architecture. The loss functions of discriminator D and generator G are included in the DCGAN's loss function. The discriminator's parameters are set after the generator has been trained. The generator's parameters are set while the discriminator is being trained.

The generator's goal is to prevent the discriminator from being able to tell the difference between generated and actual TC images as shown in Eq. (5).

$$L_D^{adv} = log(1 - D(G(X)) \qquad (5)$$

The discriminator can be tricked by the generator by minimizing Eq. (6), which prevents the discriminator from differentiating between generated and real images. The L1 loss function is then presented in order to calculate the difference between the generated and actual images as shown in Eq. (7).

$$L_1 = \sum_{a=1}^{q_w}\sum_{b=1}^{q_h}\left||G(X)(a,b) - Y(a,b)|\right|_1 \qquad (6)$$

$$L_G = \lambda_1 L_D^{adv} + \lambda_2 L_1 \qquad (7)$$

where, the empirical weight parameters are λ_1 and λ_2. By reducing Eq. (8), the generator can produce high-quality images.

Differentiating between the generated and actual images is the aim of the discriminator D. The discriminator's adversarial loss function is as follows in order to accomplish this goal:

$$L_D^{adv} = -log(D(Y)) - log(1 - D(G(X)) \qquad (8)$$

In Eq. (8), an infinite situation will arise if the generated image is incorrectly judged as the real image, or if the real image is incorrectly judged as the generated image. This implies that the discriminator needs to be optimized. A progressive decrease in Eq. (8)'s value indicates that the discriminator is becoming increasingly well-trained.

In the field of agricultural yield prediction, Deep Convolutional Generative Adversarial Networks are effective instruments for feature extraction from satellite imagery. An improvement on conventional GANs, DCGANs are made expressly to extract and assimilate hierarchical features from large, complex datasets. With regard to satellite imagery, DCGANs are particularly good at identifying complex spatial and spectral features that may be difficult for traditional methods to extract. In this context, subtle patterns and nuanced information are critical for accurate yield predictions.

DCGANs are made up of a discriminator and a generator that collaborate through adversarial training. The discriminator assesses the authenticity of these generated images in comparison to real ones, while the generator attempts to replicate the true distribution of the input data by synthesizing realistic images from random noise. This competitive process forces the generator to continuously enhance its capacity to generate images that are identical to real satellite data, efficiently recognizing and encoding complex patterns present in the imagery.

DCGANs are especially useful for extracting features like crop health indicators, vegetation distribution, and soil properties when it comes to agricultural yield prediction. The model can automatically recognize and abstract complex features at different scales, capturing both local and global patterns within the satellite imagery, thanks to the hierarchical structure of the convolutional layers in DCGANs. Subsequently, these acquired characteristics can function as comprehensive depictions for subsequent assignments, contributing to precise crop yield forecasting.

The spatial relationships and contextual information found in satellite images are naturally utilized by DCGANs. Convolutional layers give the network the ability to detect spatial hierarchies, which is essential for figuring out how crops are arranged, pinpointing specific areas, and encapsulating the diversity of agricultural landscapes. As a result, the generated features offer a thorough depiction of the fundamental features and structure of the agricultural terrain, enabling more accurate yield predictions. The application of DCGANs to feature extraction from satellite imagery presents a refined method for identifying and encoding complex spatial relationships and patterns in the data. DCGANs are especially well-suited for the intricate and nuanced task of agricultural yield prediction because of their hierarchical feature learning capabilities, which provide a solid basis for further model training and optimization. The DCGAN's architectural diagram is illustrated in the Fig. 2.

D. Convolutional Neural Network for Agricultural Yield Prediction

CNNs play a pivotal role in leveraging satellite imagery to make accurate predictions. CNNs excel in learning hierarchical and spatial representations from images, making them particularly effective for capturing intricate patterns and features present in agricultural landscapes. Trained on a dataset comprised of real and synthetic satellite images, where the latter is generated using a DCGAN to augment the available data, the CNN learns to automatically extract relevant features associated with crop health, growth, and other factors influencing yield. The convolutional layers of the network act as localized feature detectors, identifying distinctive spatial patterns in the images, while subsequent layers integrate these features for high-level representation and prediction. Through this process, the CNN becomes adept at discerning subtle variations in satellite imagery, contributing to a robust and accurate model for agricultural yield prediction, which is crucial for informed decision-making in precision agriculture and resource optimization.

The source data is passed through a series of "filters" by convolutional layers. Every filter is made to identify a particular pattern or feature, like corners, edges, or, in the case of deeper layers, more intricate shapes. These filters result in a map that shows the locations of the characteristics as they move across the image. The output of the convolutional layer is a feature map, which is a representation of the source data with the filters applied. Convolutional layers can be stacked to create more complex models with a higher capacity to extract finer details from images. Convolutional layers, put simply, are in charge of extracting features from the input images. These characteristics could be corners, edges, textures, or intricate patterns. Eq. (9) represents the input pixel, filter and the value at the position

$$A(p,q) = \sum x \sum y\, B(p+x, q+y) * E(x,y) + b \qquad (9)$$

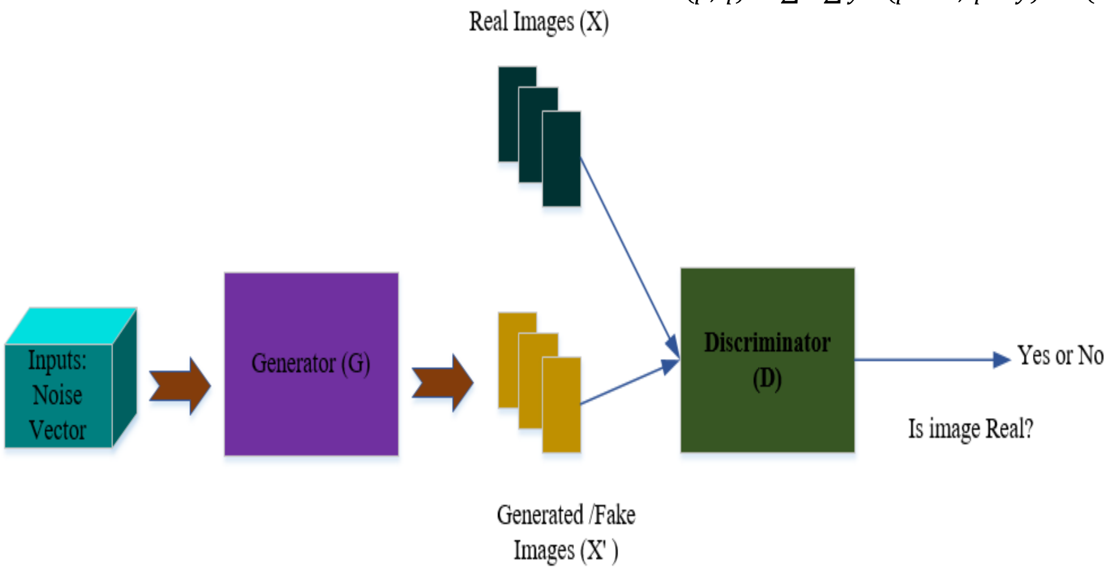

Fig. 2. DCGAN's architectural diagram.

where, A (p, q) is the value in the future map at position (x, y).

B $(p+x, q+y)$is the input image pixel at position $(p=x, q=y)$

E (x, y) is the filter/kernel at position (x, y).

b is the bias term

Pooling layers are used to speed up analysis and decrease the spatial extent of the user's input. They are the next in the processing hierarchy after convolutional layers. In the context of images, "spatial dimensions" refers to the height and width of the image. The fundamental units of an image are called pixels, which resemble rows and columns of tiny squares. By reducing the spatial dimensions, pooling layers help lower the number of factors or weights in the system. This expedites the model's training process and helps avoid overfitting. Because max pooling reduces the size of the feature map and makes the model invariant to small transitions, it aids in lowering computational complexity.

The network wouldn't be able to identify features regardless of slight rotations or shifts without max pooling. This could potentially reduce accuracy by weakening the model's resistance to changes in object positioning within the image.

For example, if the pooling window is 2 by 2, the highest-valued pixel in that 2 by 2 region will be selected. Max pooling effectively captures the most notable feature or characteristic within the pooling window. Using average pooling, the sum of all values within the pooling window is found. It provides a picture of typical, rounded features. Eq. (10) denotes the maximum pooling function. The CNN architectural diagram is given in Fig. 3.

$$F(p,q) = \max(F(2r,2s), F(2r,2r+1), F(2r+1,2s), F(2r+1,2s+1)) \quad (10)$$

E. Adam Optimization for Enhancing DCGAN-CNN Model

Adam is ideally suited for the intricate and dynamic nature of deep neural network training since it combines adaptive learning rates with momentum. The algorithm's adaptive features facilitate the efficient adjustment of learning rates for individual model parameters by utilizing the historical gradients. This leads to a stable and robust convergence. This flexibility comes in handy when working with datasets of satellite imagery, where intricate spatial patterns and variable data distributions call for an optimization algorithm that can navigate a wide range of complex and subtle terrain. Adam's scalability to manage massive amounts of high-dimensional satellite imagery data is further enhanced by its efficient memory usage, which is attained by preserving moving averages of gradients and squared gradients. Moreover, compared to conventional optimization techniques, Adam's simple implementation and reduced hyperparameter requirements make it a practical and effective option for remote sensing and agricultural analytics professionals. By using Adam, researchers and practitioners can improve DCGAN-CNN performance and training efficiency, which will lead to more accurate and dependable predictions in satellite-based applications.

It combines the advantages of momentum and Root Mean Square Propagation, two other optimization techniques. Adam works well in a range of machine learning scenarios by adjusting the learning rates of individual model parameters based on the historical gradients.

Two moving averages, one for the gradients (first moment) and another for the squared gradients (second moment), computed exponentially over time, are essential components of Adam. Setting hyper parameters during initialization includes determining the learning rate (α), the decay rate in the first moment estimate (β_1), and the decay rate in the second moment estimate (β_2). The algorithm uses exponential decay to update the first and second moment estimates at each iteration and computes the gradient of the loss with respect to model parameters. Adam presents terms for bias correction in order to address biases towards zero.

Using exponential decay, update the first moment estimate (mean of gradients) and the second moment estimate (mean of squared gradients) is expressed in Eq. (11) and Eq. (12).

$$n_t = \beta_1 . n_{t-1} + (1-\beta_1) . g_t \quad (11)$$

$$o_t = \beta_2 . o_{t-1} + (1-\beta_2) . (g_t)^2 \quad (12)$$

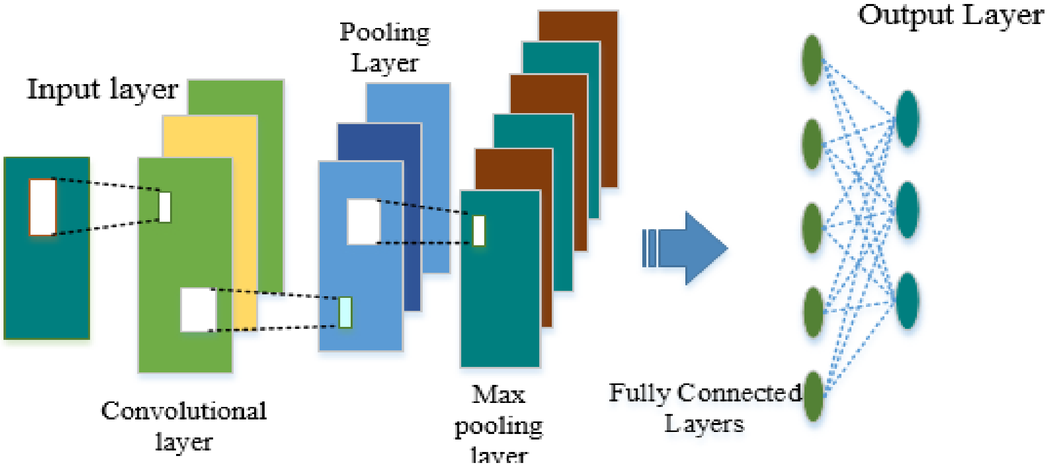

Fig. 3. CNN architectural diagram.

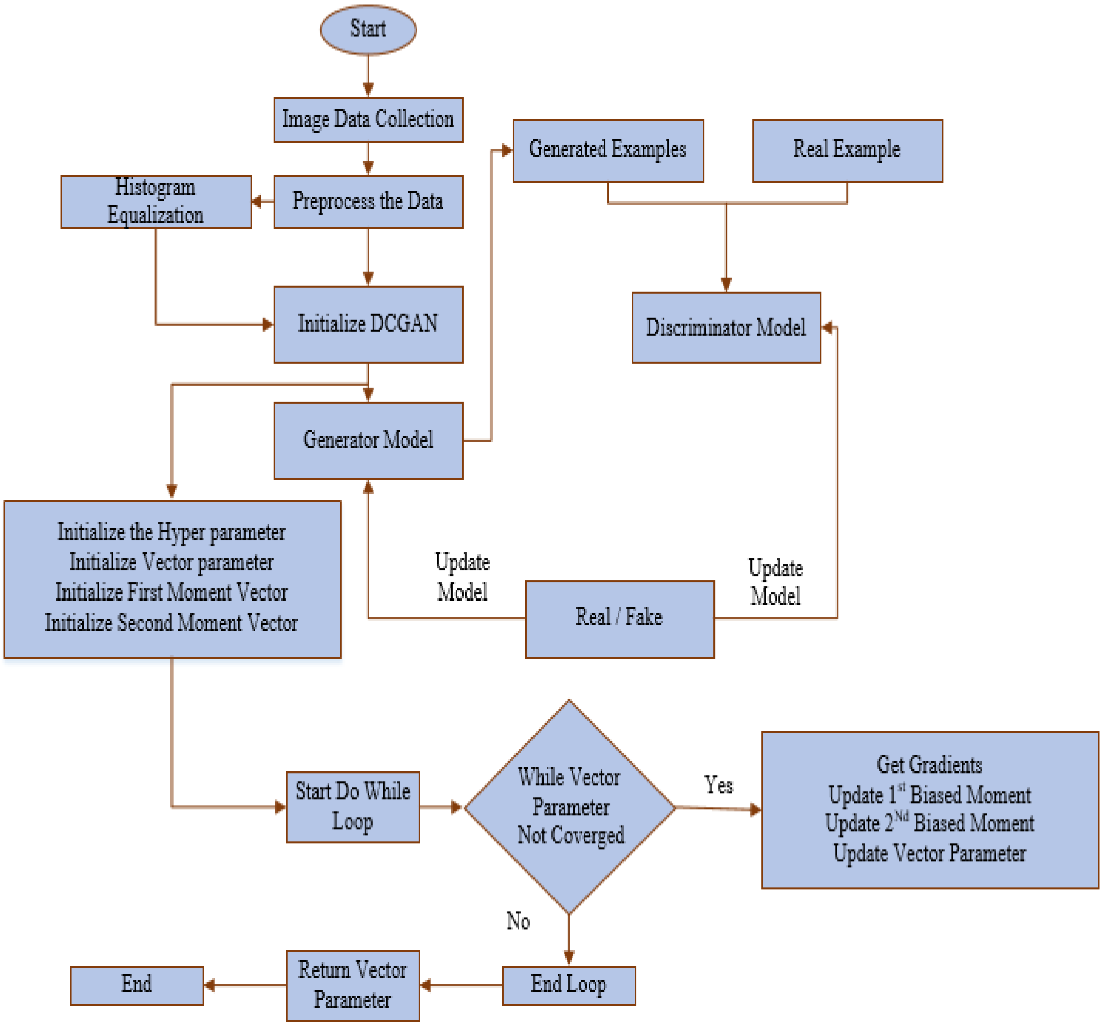

Fig. 4. Flowchart of the proposed AO optimized DCGAN method.

where, the gradient is denoted by g_t, and the first and second moment estimates at iteration t are represented by n_t and o_t, respectively. Particularly in the early iterations, there is a bias towards zero in the estimates of n_t and o_t.

Adam presents terms for bias correction in order to address this bias. Eq. (13), Eq. (14) and Eq. (15) represents,

$$\widehat{n_t} = \frac{n_t}{1-\beta_1^t} \tag{13}$$

$$\widehat{o_t} = \frac{o_t}{1-\beta_2^t} \tag{14}$$

$$\theta_{t+1} = \theta_t - \alpha.\frac{\hat{n}_t}{\sqrt{\hat{v}_t + \epsilon}} \tag{15}$$

The model parameter at iteration t is represented by θ_t, the learning rate is represented by α, and division by zero is maintained by the small constant ϵ. The final step updates the model parameters using the bias-corrected estimates. Adam is a powerful optimizer because of its adaptability, real-world efficacy, and combination of momentum and RMSprop. The best results require experimentation and fine-tuning because task-specific characteristics and hyper parameter selection determine its performance. Adam is a good neural network training optimizer due to its momentum incorporation and adaptive features. Fig. 4 shows the flowchart of the proposed AO Optimized DCGAN Method.

V. Results and Discussion

The results section presents the outcomes of the empirical analysis conducted in this study, elucidating the effectiveness and performance of the proposed methodology in agricultural yield forecasting. It provides a detailed overview of the model's predictive accuracy, robustness, and generalization capabilities across different environmental conditions and crop types. Additionally, the results section offers insights into the interpretability of the model, highlighting key features and factors influencing yield predictions, thereby contributing to a deeper understanding of the underlying dynamics of agricultural production.

In this section, the research present the results obtained from our novel approach integrating DCGANs with satellite imagery for the purpose of optimizing agricultural yield prediction. The utilization of DCGANs allowed us to generate synthetic satellite images, enabling the augmentation of our training dataset and enhance the model's ability to generalize across diverse agricultural landscapes. Through extensive experimentation, we evaluate the performance of our proposed methodology in comparison to traditional yield prediction models. Our results shed light on the efficacy of DCGANs in extracting meaningful features from satellite imagery, providing valuable insights into the potential advancements and improvements that can be achieved in the realm of precision agriculture. When combined, the metrics that the research evaluates provide a strong basis for assessing and maximizing the efficiency of DCGANs in satellite imagery-based agricultural yield prediction. The performance of the model across these crucial metrics will be thoroughly examined and its implications will be discussed in the results section that follows, providing insight into the model's potential to improve agricultural prediction processes.

A. *Performance Metrics*

Metrics that quantify the accuracy, precision, and overall efficacy of the model are essential when assessing the way a DCGAN predicts agricultural yields from satellite imagery. The objectives of the agricultural yield prediction task should be taken into consideration when designing these metrics. The following metrics are frequently employed when assessing DCGANs and contrasting them with conventional techniques

1) Mean squared error: The average squared difference between the model's predicted agricultural yield values and the dataset's actual observed yields is measured by a performance metric called mean squared error, or MSE. A lower MSE value reflects a higher degree of accuracy in the DCGAN's agricultural productivity predictions by indicating that it is better at minimizing the overall difference between predicted and true yield values. The following Eq. (16) is the formula for mean squared error:

$$MSE = \frac{1}{n}\sum_{p=1}^{n}(y_{p-}\hat{y}_p)^2 \tag{16}$$

where,

The total number of instances in the dataset is represented by n.

For p th instance, y_p represents the actual agricultural yield that was observed.

For p th instance, $\hat{y}_p$ denotes the expected yield calculated by the DCGAN.

The mean squared error (MSE) is computed by averaging the squared deviations between the observed and anticipated values for every example in the dataset. This metric provides a quantitative assessment of the model's accuracy in predicting agricultural yields by penalizing larger errors more severely.

2) Accuracy: Assessing the accuracy by contrasting the predicted class labels your model generates with the ground truth (actual) labels for your test dataset. After processing all of the test photos to determine accuracy, increase the "Number of Correct Predictions." and divide this count by the "Total Number of Predictions" if the projected label for an image in the test dataset matches the actual label. Accuracy is commonly determined by applying Eq. (17).

$$Accuracy = \frac{RN+RP}{RP+AP+RN+AN} \tag{17}$$

The accuracy metric assesses the percentage of correctly classified instances, offering valuable information about the DCGAN's capacity to identify and replicate significant patterns associated with crop yield throughout the complete dataset. A high accuracy shows that the model is able to learn and generalize from the satellite imagery in an efficient manner, resulting in dependable predictions for the evaluation of agricultural yield.

3) Precision: Precision is a commonly measured quantity, primarily in statistics and machine learning. It assesses a model's ability to make positive predictions about the future. The ratio of accurate forecasts to all reliable forecasts is known as precision. It is commonly combined with other classification model metrics like accuracy, F1-score, and recall. The formula for precision in Eq. (18) is as follows:

$$Precision = \frac{True\ Positives}{(True\ Positives+False\ Positives)} \tag{18}$$

The number of correctly predicted positive outcomes is known as True Positives. The number of negative events that the model misinterpreted as positive is known as False Positives (FP). The precision level is a number between 0 and 1, where 1 represents perfect precision (all correct positive predictions) and 0 represents no correct positive predictions. To use this equation, a dataset containing the ground truth labels and the model's predictions is required. Next, ascertain precision by counting the true positives and negatives using the previously described method.

A high precision value indicates that the DCGAN minimizes false positives by being effective in identifying regions of interest linked to high crop yield. Precision is particularly important in agriculture because it highlights the model's capacity to offer reliable and accurate insights into regions where ideal yields can be anticipated, assisting farmers and other stakeholders in making well-informed decisions.

4) Recall (sensitivity): Recall is also known as sensitivity and true positive rate. The ability of the model to correctly identify each relevant instance of a given class that is present in the dataset is referred to as recall. It determines the percentage of true positive predictions, or correctly detected instances of a class, out of all real positive occurrences for that class. Recall can be defined as mathematically in Eq. (19)

$$Recall(sensitivity) = \frac{True\ Positives}{True\ Positives+False\ Negatives} \tag{19}$$

A high recall value means that the DCGAN minimizes false negatives by effectively capturing a sizable portion of the regions linked to optimal agricultural yields. To ensure that the model can consistently identify and highlight areas of interest in agricultural applications and help farmers and decision-makers optimize their resource allocation and management strategies, a high recall is necessary.

5) Specificity: The proportion of accurately anticipated negative observations to all actual negative observations is defined as specificity. Eq. (20) is used to compute it:

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \tag{20}$$

Specificity is frequently shown against sensitivity (True Positive Rate) at different categorization levels within the framework of the ROC curve. A high specificity number means that the occurrences of the negative class are accurately identified by the model, and they are not being incorrectly classified as positive.

6) F1-Score: The F1 score is particularly useful in datasets that are unbalanced meaning that one class significantly outnumbers the other. The following Eq. (21) is used to determine the F1 score:

$$F1\ Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{21}$$

A model that successfully strikes a balance between the accuracy of positive predictions and the capacity to record all pertinent cases is indicated by a higher F1 score, which provides a thorough indicator of overall predictive accuracy.

7) AUC: The ROC curve, which plots the True Positive Rate (sensitivity) versus the False Positive Rate (one-specificity), provides a graphic representation of a model's performance across different classification thresholds. The range of the AUC is 0 to 1, where:

The model performs no better than chance, according to an AUC of 0.5.

AUC > 0.5 denotes performance that is superior than chance, and higher values signify improved discriminative capacity.

The capacity of a model to distinguish between positive and negative occurrences, such as a DCGAN in agricultural yield prediction, an improved model's ability to distinguish pertinent agricultural features is indicated by an AUC value that is closer to 1, which makes it a useful metric for assessing the model's overall discriminatory power.

TABLE I. THE SUGGESTED METHOD'S PERFORMANCE METRICS ARE COMPARED TO THOSE OF EXISTING METHODS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
YOLO v3 [25]	93.96	80.64	85.9	89
Deep CNN [21]	96.11	90.67	93.90	89.56
Two Stage Neural network [18]	95.38	90.18	85.52	86
Proposed AO-DCGAN+CNN	98.6	98.2	97	96

Compared to YOLO v3, Deep CNN, and Two Stage Neural Network, the proposed AO-DCGAN+CNN model achieves the highest accuracy of 98.6%, outperforming the other methods is given in Table I. Compared to state-of-the-art methods, it demonstrates superior precision (98.2%), recall (97%), and F1 Score (96%), demonstrating its efficacy in precise object detection and classification.

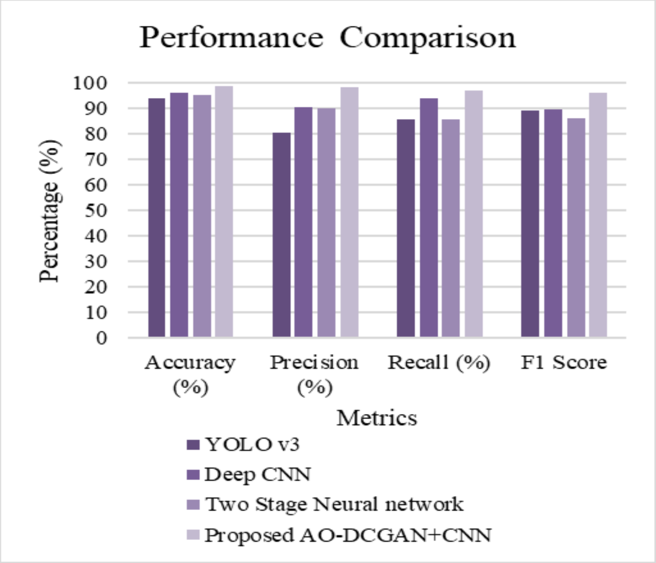

Fig. 5. Visual representation of the performance measures of the suggested DCGAN+CNN's using traditional methods.

Fig. 5 shows the performance metrics of the proposed DCGAN+CNN model in comparison to conventional techniques. The graphical representation highlights the proposed model's superior accuracy; precision, recall, and F1 score over traditional methods, demonstrating how effective it is at advancing agricultural yield prediction.

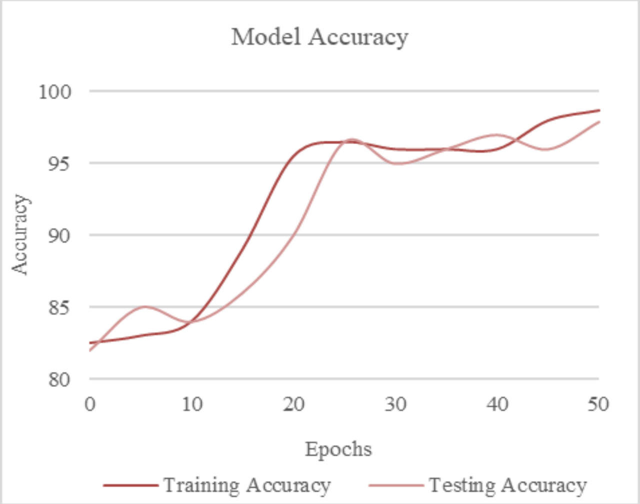

Fig. 6. The suggested DCGAN+CNN method's graphical representation for both training and testing accuracy.

The suggested DCGAN+CNN method is graphically represented in Fig. 6, which shows the accuracy of both training and testing. In addition to confirming the model's effectiveness in maintaining high accuracy during testing, the visual highlights the model's performance dynamics throughout the training process, offering insights into its learning behavior.

Table II provides an extensive analysis of the performance metrics of the Proposed DCGAN+CNN, demonstrating its superior MSE of 8.20% in comparison to conventional techniques.

TABLE II. EVALUATION OF PROPOSED DCGAN+CNN PERFORMANCE METRICS USING TRADITIONAL METHODS

Methods	MSE (%)
Random Forests	17.98
KNN	25.64
Proposed DCGAN+CNN	8.20

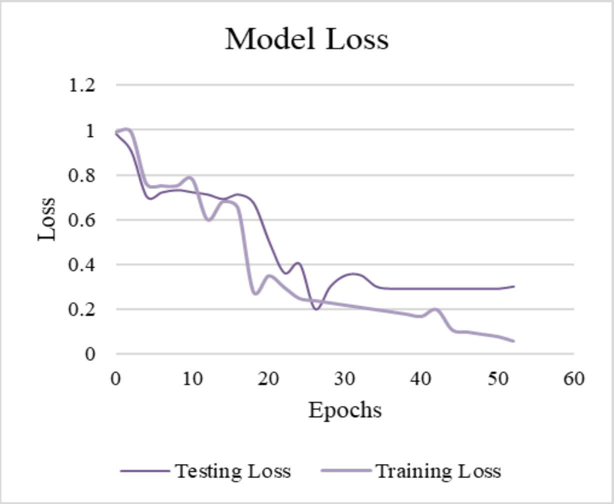

Fig. 7. The proposed Adam optimized DCGAN+CNN's training and testing loss is illustrated graphically.

The training and testing loss of the suggested Adam Optimized DCGAN+CNN model is shown graphically in Fig. 7. The graphical display provides a thorough understanding of the convergence and generalization capabilities of the model, demonstrating the efficient optimization and performance stability attained in the training and testing stages.

The ROC curve for the suggested DCGAN-CNN model is shown in Fig. 8, demonstrating how well it can differentiate between true positive and false positive rates.

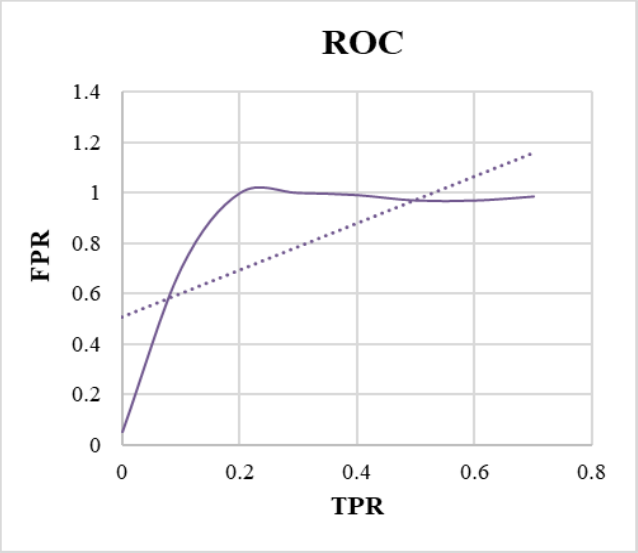

Fig. 8. The proposed DCGAN-CNN's ROC Curve.

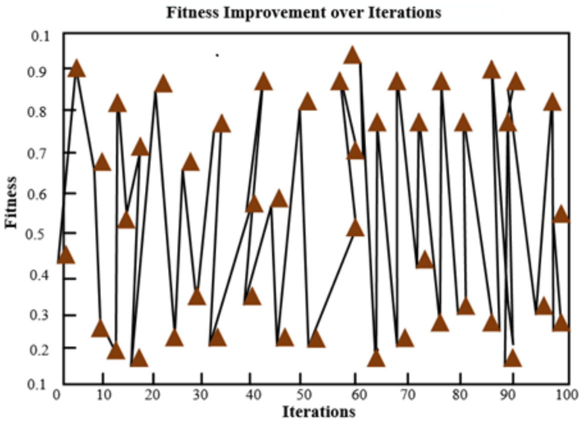

Fig. 9. Graphical illustration of proposed Adam optimizer's fitness graph.

The fitness graph for the suggested Adam optimizer is shown graphically in Fig. 9. The figure illustrates the way optimization algorithm works, highlighting how it can adjust and improve the DCGAN+CNN model's training efficiency, which leads to better overall performance in agricultural yield prediction.

B. Discussion

In order to improve agricultural yield prediction, a novel method that combines DCGANs with satellite imagery is presented in this study. By creating synthetic satellite images, DCGANs improve the training dataset and the model's ability to generalize across various agricultural landscapes. A thorough assessment of the model's effectiveness is provided by the performance metrics, which include Mean Squared Error, Accuracy, Precision, Recall, Specificity, F1 Score, and AUC. The findings show that the suggested AO-DCGAN+CNN model outperforms the current techniques, attaining high F1 Score (96%), recall (97%), accuracy (98.6%), and precision (98.2%). To further demonstrate the efficacy and learning behavior of the model, visual representations of performance metrics, training accuracy, testing accuracy, and ROC curve are provided. According to the research, there is great potential for improving precision agriculture through the integration of DCGANs with satellite imagery. This integration can provide valuable insights into managing strategies and allocating resources optimally for better agricultural yield prediction.

The performance metrics of various methods, including YOLO v3 [25], Deep CNN [21], Two Stage Neural Network [18], and the proposed AO-DCGAN+CNN, for agricultural yield forecasting is discussed. The proposed approach outperforms existing methods, achieving an accuracy of 98.6%, precision of 98.2%, recall of 97%, and F1 score of 96%. This indicates the superior predictive accuracy and robustness of the AO-DCGAN+CNN model compared to YOLO v3, Deep CNN, and Two Stage Neural Network, highlighting its potential to enhance agricultural yield forecasting and contribute to sustainable farming practices.

VI. Conclusion and Future Work

In conclusion, the integration of DCGANs, CNNs, and satellite imagery proves to be a promising approach for optimizing agricultural yield prediction. When DCGANs are used to generate synthetic images for data augmentation, the model's capacity to generalize to a variety of environmental conditions is improved, leading to predicted outcomes that are more accurate. Using CNNs makes it easier to extract features that are useful for crop health assessment, as they can capture complex patterns and spatial representations. The model is even more flexible in different lighting conditions appreciations to the pre-processing method of histogram equalization. The framework that has been suggested exhibits promise in tackling issues related to unequal distributions of pixel intensity in satellite imagery. In the future, the scope will include investigating more sophisticated methods to improve model performance and generalization across various geographic locations, such as transfer learning and attention mechanisms. Furthermore, the model's predictive abilities could be improved by adding weather parameters and real-time satellite data, which would make it a useful tool for precision agriculture in the face of changing climate conditions. It is possible to improve agricultural technology, guarantee food security, and promote sustainable farming practices by carrying out more research in this area. Despite the promising results, several limitations and avenues for future research exist in enhancing agricultural yield forecasting with DCGANs and satellite data. Firstly, the effectiveness of the proposed approach may be influenced by the availability and quality of satellite imagery, as well as the heterogeneity of agricultural landscapes. Future work could focus on addressing these challenges through the development of more sophisticated DCGAN architectures capable of generating higher-fidelity synthetic images and incorporating additional environmental variables for improved accuracy. Furthermore, research could explore the integration of real-time weather data and other relevant agricultural indicators to enhance the predictive capabilities of the model. Additionally, there is a need for comprehensive validation and verification of the proposed approach across diverse geographical regions and crop types to ensure its generalizability and robustness. Finally, investigating the scalability and computational efficiency of the model for large-scale applications would be beneficial for practical deployment in agricultural decision-making and policy formulation.

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Analyzing Multiple Data Sources for Suicide Risk Detection: A Deep Learning Hybrid Approach

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***Abstract*—In the current digital landscape, social media's extensive user-generated content presents a unique opportunity for identifying emotional distress signals. With suicide rates on the rise, this study takes aid of Natural Language Processing (NLP) and Sentiment Analysis to detect suicide risk. Centering primarily around deep learning (DL) architectures, including Convolutional Neural Network (CNN), Bidirectional Gated Recurrent Unit (Bi-GRU) and their combined hybrid BiGRU-CNN model, the research incorporates machine learning (ML) for comparative analysis through multisource datasets from Reddit and Twitter. The methodology commenced with data pre-processing, followed by exploring word embedding techniques. This research included an analysis of both Word2Vec variants as well as pretrained GloVe embeddings, where Skip-Gram paired with Adam optimizer showed superior results. For thorough evaluation, Receiver Operating Characteristic (ROC) curves, Confusion Matrix and Accuracy-Loss graphs were utilized. Furthermore, generalizability of employed models was testified and evaluated by in-depth inspections. The process was accomplished by activating manual input test, cross dataset test and k-fold cross validation procedures. In the course of scrutinizing, the proposed BiGRU-CNN model outperformed the traditional DL and ML models with consistent and reliable performance. Correspondingly, the proposed model achieved accuracies of 93.07% and 92.47% on the respective datasets which advocate its potential as a tool for the early detection of suicidal thought.**

Keywords—BiGRU-CNN hybrid; multisource dataset; word embeddings; NLP; sentiment analysis; cross-dataset testing

I. Introduction

Suicide is a deeply sensitive and significant issue that demands empathy and understanding. The World Health Organization (WHO) carried out a research investigation in 2021 that declares suicide as a prominent and relentless global cause of death. According to [1] and [2], annually 0.7 million people die by suicide marking it as fourth leading cause of death. Reportedly, majority of the victims fall under the age group of 15 to 29 years. Over the past 15 years, the world witnessed a 24% increase in the overall suicide rate as per The National Institute of Mental Health [3]. In the pandemic year of 2020 suicides increased by 10% from previous year in India and reached a record high of 1, 53, 052 [4].

Suicidal thoughts can arise from various factors like mental health issues, societal pressures, isolation and hopelessness. Social media platforms provide a practical angle for analyzing mental health indicators as individuals tend to often express their emotions and struggles there. Traditional methods for assessing suicide risk are often limited by their time-consuming nature and inability to detect immediate risks. This has led to a paradigm shift towards employing Artificial Intelligence (AI) for text analysis as AI promises enhanced accuracy and efficiency. Human emotions from textual data now can be deciphered by automated system with the help of evolving areas of NLP [5] and Sentiment Analysis [6].

This research sought to detect early signs of suicidal thoughts by developing an automated system. The study proceeded with collecting data from social media platform like Reddit and Twitter. Consequently, the effectiveness of DL architectures was evaluated, particularly CNN, Bi-GRU along with their combined hybrid BiGRU-CNN model. These models were chosen due to their ability of extracting local features and capturing sequential, contextual information from text. ML models including Linear Support Vector Classifier, Logistic Regression, Decision Tree and AdaBoost were selected. Additionally, the study conducted a performance comparison of the proposed hybrid model against these traditional ML and DL algorithms to establish a benchmark. Metrics such as accuracy, precision, recall and F1-scores were evaluated to assess the model's performance.

By addressing the research objective, this study aims to create an automated system that scans social media content to identify early signs of suicidal thoughts and provide a tool for suicide risk detection. This system ought to underscore the significant implications for helping people struggling with suicidal thoughts. The proposed model is anticipated to aid in timely interventions to support individuals who are exhibiting signs of distress on social media platforms.

The core contribution of this work was in implementing the proposed hybrid BiGRU-CNN model, employing both ML and DL models, experimenting upon multiple datasets, conducting trials on various word-embedding techniques and performing cross-dataset test by taking advantage of multi-source data. Moreover, this work assessed and verified the potential of the generalization ability of the models through cross-validation and manual dataset creation. The study demonstrated the superiority of the proposed model through these meticulous process for suicide detection across both datasets. These processes ensure a significant improvement over existing research that often overlook or insufficiently emphasize these vital facets.

The structure of our research paper is methodically organized into following key sections: Section II reviews the relevant existing work. Section III thoroughly describes the employed methodology and explains carried out experiments. Section IV presents the outcomes of the various architectures tested as well includes an in-depth analysis. Section V provides an interpretation of the discussion. The paper concludes with Section VI, summarizing the findings. Conclusively, Section VII suggests future research.

II. Related Work

We explored the extensive research on depression and suicide risk detection. To capture insights within this domain, we studied researches working on a wide range of methods and data sources.

The research outlined in study [7] explored potential suicidal thoughts in 49,178 tweets using text preprocessing techniques and feature extraction methods. Various DL techniques were trained including LSTM, Bi-LSTM, GRU, Bi-GRU, and a hybrid CNN-LSTM to check the proficiency. Upon evaluation, the Bi-LSTM model stands out with a high accuracy of 93.6% in handling the nature of tweet data.

In study [8], the authors proposed a hybrid model combining CNN with Bi-LSTM to detect depression from Twitter data. The proposed model outperformed traditional RNN and CNN models, achieving a remarkable accuracy of 94.28%.

Another study utilized Reddit data to test the LSTM-CNN hybrid model through the use of Word2Vec embedding techniques. The outshining results confirmed the model’s usefulness in text classification [9].

The authors of study [10] predicted text data-based depression with proposed RNN-LSTM techniques, using one-hot approach. Considered data was collected from Kaggle and processed via stemming and lemmatization. The proposed technique proved its ability with a commendable accuracy, excelling other methods like Naive Bayes, Support Vector Machine (SVM), CNN, and Decision Trees.

The investigator’s work in study [11] employed various text representation techniques like TF-IDF and Word2Vec, along with a combination of DL (CNN-BiLSTM) and ML (XGBoost) algorithms for text classification.

In contrast to other research, the study [12] applied text mining techniques and numerous algorithms to categorize Cantonese YouTube comments for suicide risk. The paper handled data imbalance using re-sampling and focal loss methods, resulting in g-mean scores of 84.3% and 84.5% for the LSTM model. The best performing model demonstrates the potential for effective automatic suicide risk detection in social media content.

While comparing with SVM, CNN, LSTM and LSTM-CNN combined model, the findings of [13] showcased the efficacy of LSTM-attention-CNN model with 90.3% accuracy. The researchers extracted the Reddit dataset with the assistance of Reddit API to train their employed models.

These previous researches have made significant contributions to the field of suicide detection. However, several limitations exist including reliance on single dataset that may limit the generalizability of their findings and limited exploration of word embedding techniques. Most studies have solely focused on either ML or DL model for their analysis, thereby overlooking the potential benefits of integrating both approaches.

Building upon the strengths of previous research in suicide detection, this study aimed to address key limitations through a comprehensive approach. To get a broader understanding of how people express themselves in different contexts, this research used multiple datasets from various platforms, like Reddit and Twitter. Instead of relying solely on training and testing within the same dataset, a novel cross-dataset testing methodology was implemented. Here, the model was trained on one dataset and then tested on others. This innovative testing process helps in understanding the model’s adaptability in real-world applications. Additionally, the study went beyond the commonly used Word2Vec technique and also incorporated pre-trained GloVe embeddings to allow the model to capture meaning from the text.

By addressing these limitations and employing these approaches, our research intends to contribute meaningfully to the advancement of suicide detection and mental stability observation.

III. Experimental Methodology

A. Origin of Data

This study operated on multi datasets for the purpose of ensuring diverse and comprehensive collection of textual content related to mental health and suicidal thought. The Reddit dataset was obtained from the “Suicide Watch” section on Kaggle.[1] It consists of a balanced collection of 232,074 posts which was equally divided with 116,037 posts each in the ‘suicide’ and ‘non-suicide’ categories. Additionally, the Twitter dataset was collected from a GitHub repository.[2]It comprises 9,119 tweets and categorized as 5,121 non-suicidal (0) and 3,998 suicidal (1) tweets. The deliberate selection of data from multiple platforms was critical for the models in understanding the expressions of suicidal thought. Table I carries a general overview about the utilized datasets by presenting few sample texts along with their assigned class labels.

TABLE I. Sample Text of Suicidal and Non-suicidal Context

Dataset	Text	Class
Reddit	It ends tonight. I can’t do it anymore. I quit.	Suicide
	Its almost 2 am Why am I tired?? It's so early damn	Non-suicide
Twitter	i am looking for someone to talk to all i want to do is die	1
	attempting a poetry essay listening to jessie rose and feeling fat	0

B. Data Preprocessing

Real-world data often comes in a messy and unorganized form with mistakes and irrelevant details. This complexity and inconsistency can negatively impact in model’s ability and lead to inaccurate predictions. Pre-processing is a fundamental step that converts those raw data into structured format and positively influence the efficacy of the models.

[1] https://www.kaggle.com/datasets/nikhileswarkomati/suicide-watch
[2] https://github.com/laxmimerit/twitter-suicidal-intention-dataset

In our study, the process initiated by removing accented characters and expanding contractions to standardize text expressions. Successively stopwords, symbols URLs, digits, and special characters was discarded to eliminate noise from data. Further refinement included lemmatization, correction of spelling mistakes, and word lengthening. Irreverent words and posts with no content were excluded to eliminate potential noise and bias in the datasets. With the help of a sample text, the process is depicted in Fig. 1. Here red box contains the raw text and cleaned text is presented in the green box.

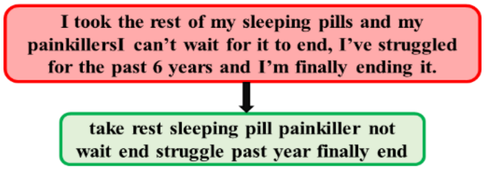
I took the rest of my sleeping pills and my painkillersI can't wait for it to end, I've struggled for the past 6 years and I'm finally ending it.
take rest sleeping pill painkiller not wait end struggle past year finally end

Fig. 1. Sample of preprocessing technique.

Reddit dataset consisted an unnamed column that was irrelevant to this task and was dropped in the cleaning step. After performing data cleaning, Reddit dataset exhibited a class imbalance with 'suicide' posts at 38.9% and 'non-suicide' at 61.1%. The imbalance arose due to original dataset had several 'suicide' labelled rows without any corresponding texts. Consequently, under-sampling was introduced to tackle the potential bias toward the majority class and improve model's performance. Collectively, these preparations were pursued to enhance the model's capability for accurate understanding and detection of the texts.

C. Word Embeddings

Word embedding [14] techniques provide a means of converting textual data into numerical form so that semantic meanings and relationships between words can be captured. This paper exploited both approach of Word2Vec, namely Skip-Gram and Continuous Bag of Words (CBOW) methods to turn words into useful vectors and trained on cleaned-up text from Twitter and Reddit. Moreover, GloVe (global vectors for word representation) embeddings was explored as well, specifically the GloVe 6B dataset collected from online.[3] The pre-trained models such as GloVe present an extensive vocabulary with vectors trained on a vast corpus, therefore, offer a profound source of semantic data.

D. System Overview with Classifiers

The core of our methodology was characterized by the deployment of both ML and DL models along with several word embedding techniques. The architecture in Fig. 2 summarized this entire process, highlighting the systematic and data-driven approach of our research where BiGRU-CNN was denoted as "Hybrid" and AdaBoost was as "Ensemble" methods.

After collecting and pre-processing the data, cleaned data was split into training, validation and testing sets. Following that, training and validation datasets underwent word embedding process through tokenization, effectively transforming the textual data into vector representations. Subsequently, these vectorized data were utilized to train and validate the models. Based on the validation and testing accuracies, manual hyper-parameter tuning was performed. Moreover, the models went under Cross-validation to understand their performance against different subsets of the data. To analyze the effectiveness of the models against unseen data, manual text input was provided for predicting. On top of that, cross-data testing strategy was implemented to ensure versatility, where models were trained on one dataset and tested against the other. Upon performance comparison, the best model was then chosen as proposed model.

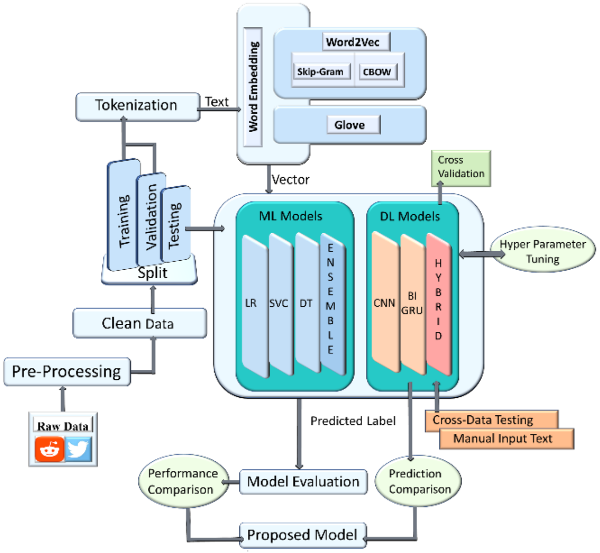

Fig. 2. Architecture of the proposed system.

1) BiGRU-CNN:

The proposed model architecture depicted in Fig. 3 combined the features of Bi-GRU and CNN with a view to improve the capability of classifying suicidal text.

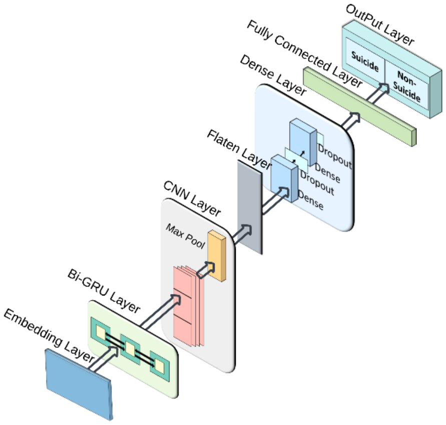

Fig. 3. Proposed model architecture.

While implementing the hybrid model, initially an embedding layer was established that converted text into dense vectors through word embedding. Building on this, a Bi-GRU layer intricately processed these embeddings, capturing the textual context from both forward and backward directions. Thus, it formed a more elaborate representation of the input sequence. The subsequent Conv1D layer applied convolutional

[3] https://nlp.stanford.edu/projects/glove/

operations with multiple filters which proficiently identified and extracted key local features and patterns that were indicative of suicidal thought. Thereafter, dimensionality reduction was achieved through a MaxPooling layer, followed by flattening for dense layer compatibility. Ultimately, dense layers with dropout regularization guided to the output layer, where a sigmoid activation function was employed to compute the probability of suicidal thought.

The layers and parameters along with their corresponding values are tabularized in Table II.

TABLE II. PARAMETERS USED IN PROPOSED MODEL

Layers	Parameters	Values
Embedding	Embedding Dimension	100
Bi-GRU	Units	64
	Dropout Rate	0.25
Conv1D	Filters	128
	Kernel Size	3
	Activation Function	ReLU
MaxPooling1D	Pool Size	2
Dense	Units	128, 64
	Activation Function	ReLU
	Regularization	L2 (0.01)
Dropout	Dropout Rate	0.5
Output	Activation Function	Sigmoid
	Optimizer	Adam
	Loss Function	Binary Cross-entropy
	Batch Size	Twitter Dataset (32)
		Reddit Dataset (128)
	Epoch	20

In our study, we Initialized embedding layer with weights and embedding dimension from the pre-trained Word2Vec and GloVe models. It acts as:

$$Embedded(i) = EmbeddingMatrix[i] \tag{1}$$

Here, i is the word index and $EmbeddingMatrix$ is a matrix of shape containing the learned word embeddings.

The Bi-GRU augments the Gated Recurrent Unit (GRU) by processing data in opposite directions. Prior to exploring the Bi-GRU, we will examine the equations that govern a standard GRU.

For a single GRU cell, the following equations define its operation. Here z_t represents the update gate, r_t denotes the resent gate, σ signifies sigmoid activation function, $\tilde{h}_t$ stands the potential hidden state for the current node in the hidden layer, h_t is the hidden state at time t, and h_{t-1} is the input at time is the hidden state of the previous time step. w and u are weight matrices.

$$z_t = \sigma\,(w_{zx}x_t + u_{zh}h_{t-1}) \tag{2}$$

$$r_t = \sigma\,(w_{rx}x_t + u_{rh}h_{t-1}) \tag{3}$$

$$\tilde{h}_t = \tan\,(w_{hx}x_t + r_t * u_{hh}h_{t-1}) \tag{4}$$

$$h_t = (1 - z_t) * \tilde{h}_t + z_t * h_{t-1} \tag{5}$$

In a Bi-GRU, these operations are performed in two separate GRUs: one processing the sequence from start to end ($h_t^{forward}$) and the other from end to start ($h_t^{backward}$). The final hidden state (h_t) for each time step is a concatenation of these two directional hidden states:

$$h_t = [\,h_t^{forward};\ h_t^{backward}\,] \tag{6}$$

Each GRU in the Bi-GRU has its own set of parameters, and they are trained to capture temporal dependencies in both directions of the input sequence.

Following the Bi-GRU layer, the Conv1D layer applies a 1D convolution operation with $relu$ activation function applied afterwards. $K(u)$ embodies the value of kernel at position u and $I(i+u)$ is the input feature at position $i+u$.

$$F(i) = \sum_{u=0}^{Kernel\_size-1} I(i+u).K(u) \tag{7}$$

$$relu(x) = \max(0, x) \tag{8}$$

After that, max pooling operation was performed over the 1D input. For input feature map F, pooling size $poolsize$, and output feature map P, the max pooling operation at position (i) is:

$$P(i) = \underset{0 \leq u < poolsize}{max} F(i+u) \tag{9}$$

The Flatten layer simply reshaped the output to a single dimension. Dense layers performed linear transformation followed by $relu$ activation, with $L2\ Regularization$ applied to the weights w:

$$Flatten(F) = Reshape\ to\ 1D(F) \tag{10}$$

$$y = relu(w_x + b) + L2\ Regularization \tag{11}$$

To conclude the model, a sigmoid activation function was used to provide the probability of the text indicating suicidal ideation.

The proposed model's ability to understand both the context and specific language signs in social media data makes it suited for identifying potential signs of suicidal thought.

Beyond the proposed model, our study explored additional models to comprehensively analyze suicide risk, including:

2) CNN: Designited for its intriguing ability to detect local patterns and features in textual data [15]. The arhitecture consisted of a 100-dimentioal embedding layer to encode words, followed by a Conv1D layer with 128 filters of size 3 and for feature extraction ReLU activation function was applied. To prevent overfitting, the model included MaxPooling1D and Dropout layers. Other configurations remained similar to the proposed model. CNN model was utilized through the layers and parameters that are shown in Table III.

TABLE III. OPERATIONAL DETAILS OF CNN MODEL

Layers	Parameters	Values
Embedding	Embedding Dimension	100
Conv1D	Filters	128
	Kernel Size	3
	Activation Function	ReLU
MaxPooling1D	Pool Size	2
Output	Activation Function	Sigmoid

3) Bi-GRU: Chosen for its proficiency in capturing contextual information from text sequences in both forward and backward directions [16]. The Bi-GRU model also employs a 100-dimentional embedding layer simmilar to CNN and proposed model. It incorporated two BiGRU layers with 128 and 64 units and recurrent connections for bidirectional sequence processing. The dense and dropout layers, optimizer, loss function, batch sizes, and epochs are retained as in the CNN configuration. Table IV illustrates the values of parameters used in Bi-GRU model.

TABLE IV. OPERATIONAL DETAILS OF BI-GRU MODEL

Layers	Parameters	Values
Embedding	Embedding Dimension	100
Bi-GRU Layer	Units	128,64
	Dropout	0.25
	Recurrent Dropout	0.25
Output	Activation Function	Sigmoid

4) Linear Support Vector Classifier (Linear SVC): Employed for its effectiveness in binary classification of textual data. In our context, the below mentioned decision function was used to predict the new data points classes that were fed into the Linear SVC model.

$$f(x) = sign\ (w.x + b) \tag{12}$$

where, $f(x)$ is the decision function that determines the class of a new data point $x. sign(\ )$ function assigns a class based on the sign of the result.

5) Logistic Regression (LR): Applied due to its simplicity and efficiency in probabilistic prediction.[4] The LR model is suitable for binary classification tasks like distinguishing between suicidal ideation and general content in our datasets. This is achieved through the logistic function, formally represented as:

$$P(Y = 1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2 \cdots\cdots \beta_n X_n)}} \tag{13}$$

Here, $P(Y = 1|X)$ is the probability that the dependent variable Y is equal to 1, given the independent variables $X. \beta_0$ is the intercept and e is the base of the natural logarithm. The prediction is typically classified as 1 (suicide class) if $P(Y = 1|X)$ is greater than 0.5, and as 0 (Non-suicide class) otherwise.

6) Decision Tree (DT): Chosen for its ability to understand complex language structures and relationships [17]. DT aids in suicide risk assessment through decision paths.

7) AdaBoost: Selected to enhance the performance of decision trees. The ensemble method combines multiple weak learners to form a strong classifier and improve the accuracy of suicide risk predictions from textual data [18].

The most representative equation for AdaBoost classifier is the final model decision function. It is a weighted sum of the weak classifier's decisions characterized as:

$$H(x) = sign(\sum_{t-1}^{T} \alpha_t \cdot h_t(x)) \tag{14}$$

In the equation (1.14), $H(x)$ represents the final decision function of the AdaBoost classifier and T is the total number of weak classifiers used. In this study, the value of T was specified as 50. α_t denotes the weight of the 't' th weak classifier in the ensemble.

As hyperparameter tuning, the parameters including batch size, epoch, optimizer, dropout rate, kernel size, and hidden units were systematically adjusted. After identifying the best combined parameters, the performance of all models was evaluated.

IV. RESULT ANALYSIS

Following precise pre-processing and data cleaning, the model training and evaluation phases proceeded. The process began by allocating 70% of the data for training, 20% for validation, and 10% for testing. This division was designed to rigorously assess model's performance and generalizability.

The procedure of result analysis initiated with Word clouds generation for each class. The word clouds provided a visual representation of word frequencies. They were created using the 'WordCloud' library for displaying words with sizes proportional to their frequency in the texts. This approach highlighted the most prominent words in larger fonts, allowing for easy identification of key terms characteristic of suicidal and non-suicidal texts. The clouds of each context for both datasets are shown in Fig. 4.

As this task primarily centered around DL techniques, performance of the DL models was examined and evaluated subsequently. Table V provides a detailed breakdown of evaluation metrices. For Reddit dataset, the proposed model exhibited the highest accuracy of 93.07%. Accrued F1-score of 0.93 indicates a balanced precision-recall relationship. The performance of the proposed model remained notable on the Twitter dataset as well, with an accuracy reaching 92.47% and mentionable precision and recall for both classes. With consistent performance against both datasets, the model establishes its strength in classification tasks.

In examining word embedding's influence on model efficacy, outcomes revealed the prominence of Skip-Gram method over alternative techniques such as CBOW and GloVe embeddings. This finding emerged as the most effective, leading the study for further analysis.

[4] https://machinelearningmastery.com/logistic-regression-for-machine-learning/

Fig. 4. Word clouds of a) Reddit b) Twitter.

TABLE V. RESULTS OBTAINED FROM DL MODELS

Data set	Models	Class	Precision	Recall	f1-score	Accuracy
Reddit	CNN	Suicide	0.92	0.91	0.92	91.30%
		Non-suicide	0.91	0.91	0.91	
	Bi-GRU	Suicide	0.93	0.92	0.92	92.12%
		Non-suicide	0.91	0.92	0.92	
	Proposed model	Suicide	0.93	0.94	0.93	**93.07%**
		Non-suicide	0.93	0.92	0.93	
Twitter	CNN	1	0.94	0.83	0.88	89.28%
		0	0.86	0.95	0.90	
	Bi-GRU	1	0.93	0.88	0.90	91.11%
		0	0.89	0.94	0.92	
	Proposed model	1	0.94	0.90	0.92	**92.47%**
		0	0.92	0.94	0.93	

On a different note, we operated two distinct optimizers: Adam and Stochastic Gradient Descent (SGD). The empirical findings indicated that the Adam optimizer continually outclassed SGD in terms of model's accuracy, securing its selection as the preferred optimizer. Table VI is showcasing the consequences.

TABLE VI. CHOOSING WORD-EMBEDDINGS AND OPTIMIZERS

Dataset	Methods	**Skip-Gram**		CBOW	GloVe
		SGD	**Adam**		
Reddit	CNN	90.85%	**91.30%**	90.52%	89.81%
	Bi-GRU	91.44%	**92.12%**	91.28%	90.75%
	Proposed Model	91.77%	**93.07%**	92.77%	92.36%
Twitter	CNN	88.25%	**89.28%**	87.34%	88.48%
	Bi-GRU	88.37%	**91.11%**	88.60%	89.17%
	Proposed Model	89.40%	**92.47%**	89.97%	90.19%

To obtain a deeper understanding of the capabilities of DL models, the accuracy-loss curve, confusion matrix and ROC curve were generated and inspected.

The ROC curves illustrated in Fig. 5 provides a visual representation of the ability of implemented classifiers to discriminate between suicide and non-suicide instances. Area under the curve (AUC) indicating the overall performance. Observing the outcomes, it is apparent that the proposed model demonstrates the highest discriminative power. The model reaches AUC values of 0.9797 and 0.9745 for Reddit and Twitter datasets, respectively. Being compared to the CNN and Bi-GRU models, performance of the proposed approach underscores the usefulness in capturing the complexities of both datasets.

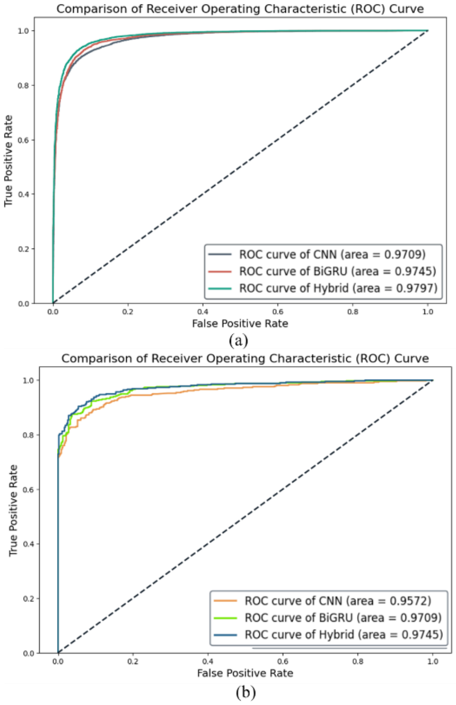

Fig. 5. ROC curves of (a) Reddit (b) Twitter.

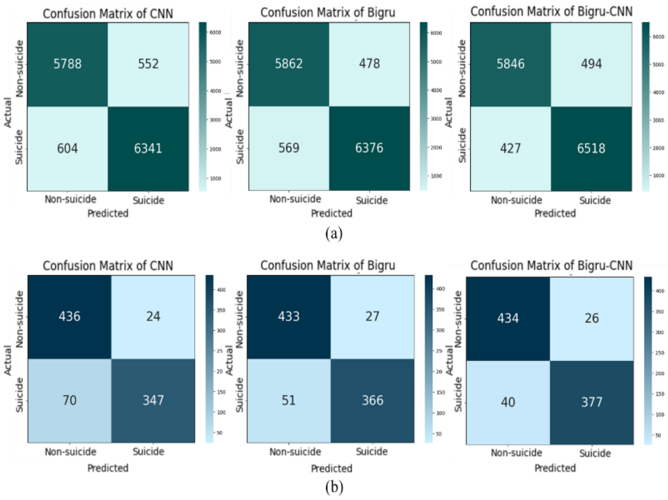

Fig. 6. Confusion matrices of (a) Reddit (b) Twitter.

We utilized confusion matrix to assess the effectiveness of our implemented models. The confusion matrix offers insights into true and false predictions and helps us understanding our model's performance. Derived metrics like precision, recall, accuracy, and F1-score gave a complete view of each model's capabilities and limitations. Fig. 6 showcases the confusion matrices for CNN, Bi-GRU, and BiGRU-CNN, starting from left.

In addition, the accuracy-loss curves in Fig. 7 and Fig. 8 guided the decision on when to stop training for avoiding overfitting. The early stopping technique was employed based on the validation loss. Here, the accuracy curve illustrated the percentage of accurate predictions in both training and validation phases. The loss curve indicated the extent to which the model's predictions differ from the actual values.

With the aim of further authenticating the performance of the models, a manual dataset was created containing twenty texts. The outcome is tabularized in Table VII that portrays five texts along with assigned labels and corresponding predicted labels by the models. The left most column of the table, indicates the dataset that the models were trained on prior to manual input testing. It is apparent to note that, the proposed model demonstrated comparatively satisfactory performance in this regard as well. The proposed model that was trained on the Reddit dataset was accurate in every prediction, whereas, Twitter trained proposed model predicted one suicidal text incorrectly.

Cross -dataset testing was executed to prolong the layers of rigorous scrutiny on model's resilience. To do so, models were tested by data they have not encountered during training. For instance, models trained on the Reddit dataset underwent testing against the Twitter test split and vice versa. The corresponding values presented in Table VIII revealed the proposed model's strong adaptability against the others.

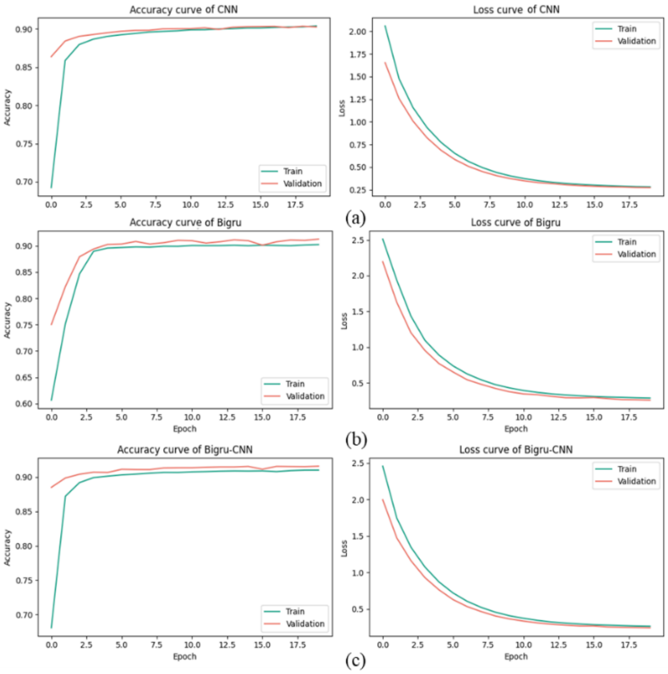

Fig. 7. Curves of (a) CNN (b) Bi-GRU (c) Proposed model of Reddit.

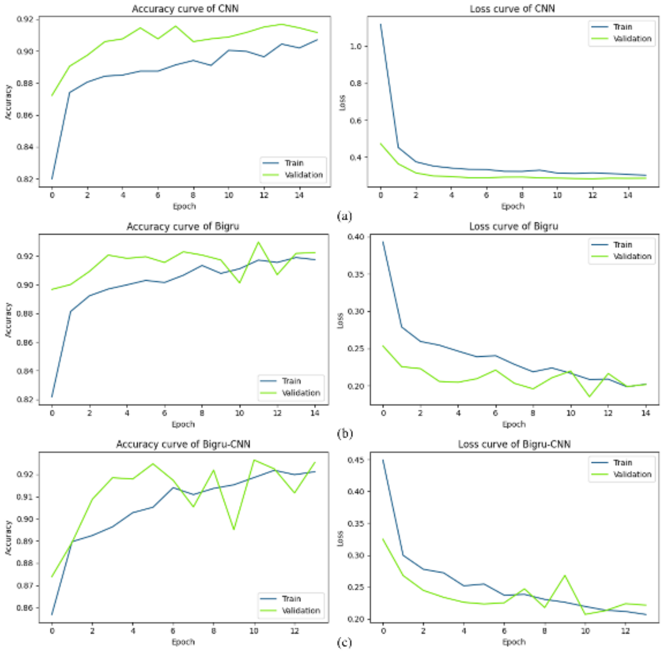

Fig. 8. Curves of (a) CNN (b) Bi-GRU (c) Proposed model of Twitter.

TABLE VII. PREDICTED RESULTS OF MANUAL INPUT TEXT

Trained On	Text	Actual Label	Predicted Label		
			CNN	Bi-GRU	Proposed Model
Reddit	Recommend pill to suicide	Suicide	Non-Suicide	Suicide	Suicide
	Don't tell me what to do. I am depressed	Suicide	Suicide	Suicide	Suicide
	The sun is shinning	Non-Suicide	Non-Suicide	Non-Suicide	Non-Suicide
	I want to end my life	Suicide	Non-Suicide	Non-Suicide	Suicide
	Going to commit suicide. No more toxicity.	Suicide	Suicide	Suicide	Suicide
Twitter	Recommend pill to suicide	Suicide	Non-Suicide	Non-Suicide	Non-Suicide
	Don't tell me what to do. I am depressed	Suicide	Non-Suicide	Suicide	Suicide
	The sun is shinning	Non-Suicide	Non-Suicide	Non-Suicide	Non-Suicide
	I want to end my life	Suicide	Non-Suicide	Non-Suicide	Suicide
	Going to commit suicide. No more toxicity.	Suicide	Suicide	Suicide	Suicide

As a final validation step to ensure model's reliability, K-fold cross-validation was implemented. The cross-validation determined the stability and consistency of models across multiple subsets of data.[5] This method systematically availed one-fold for testing and the rest for training and then averaged the results. The findings are structurally compiled in Table IX.

[5] https://machinelearningmastery.com/k-fold-cross-validation/

The data reveals a decline in accuracies with an increase in number of folds.

TABLE VIII. CROSS DATASET TESTING

Trained with	Tested By	Test Data Descriptions		Models Performance		
				CNN	Bi-GRU	**Proposed Model**
		Actual Class Distribution		Correctly Predicted Class		
Reddit	Twitter	0	460	246	274	319
		1	417	385	370	347
Accuracy				71.95%	73.43%	**75.94%**
Twitter	Reddit	Non-Suicide	6340	4228	4068	3994
		Suicide	6946	5209	5428	5593
Accuracy				71.04%	71.48%	**72.16%**

TABLE IX. PERFORMANCE THROUGH CROSS-VALIDATION

Folds	Reddit		Twitter	
	Model	Mean Accuracy	Model	Mean Accuracy
K=5	CNN	90.71%	CNN	88.95%
	Bi-GRU	91.68%	Bi-GRU	89.68%
	Proposed Model	**92.07%**	**Proposed Model**	**90.25%**
K=10	CNN	90.53%	CNN	88.78%
	Bi-GRU	91.57%	Bi-GRU	89.53%
	Proposed Model	**91.72%**	**Proposed Model**	**89.64%**

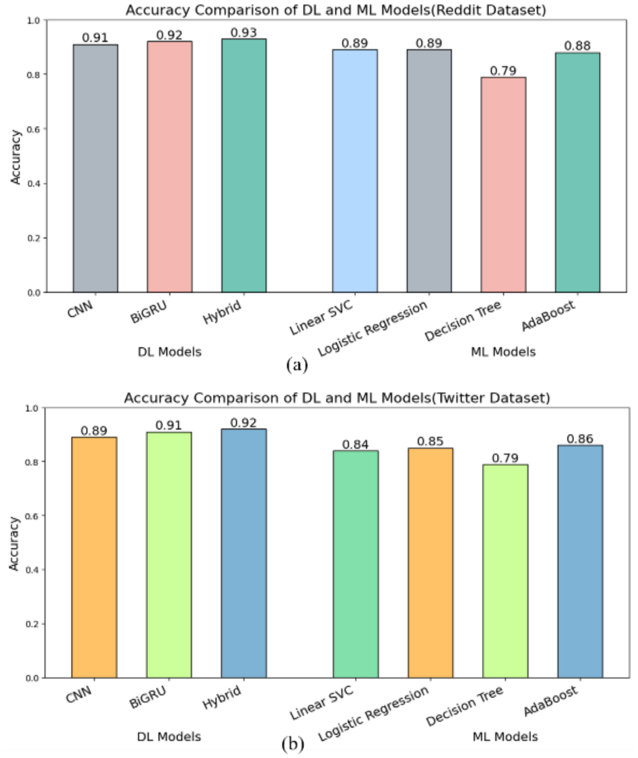

Fig. 9. Accuracy comparison among DL and ML of (a) Reddit (b) Twitter.

The research concluded with performing a comparative analysis of ML models to assess their respective effectiveness compared to Dl models. Therefore, four traditional ML models were accounted for. The performance analysis is visually portrayed with a bar chart presented in Fig. 9 which explicitly demonstrates the supreme accuracy of DL models for both datasets. It highlights the effectiveness of DL approaches over ML models in predicting suicidal contents.

A complete synopsis of the outcomes acquired from ML models, including evaluation metrices, is systematically tabulated in Table X.

TABLE X. RESULTS OBTAINED FROM ML MODELS

Data set	**Models**	**Class Label**	**Precision**	**Recall**	**f1-score**	**Accuracy**
Reddit	Linear SVC	Suicide	0.83	0.81	0.82	88.55%
		Non-suicide	0.91	0.92	0.92	
	LR	Suicide	0.84	0.80	0.82	88.55%
		Non-suicide	0.91	0.93	0.92	
	DT	Suicide	0.66	0.69	0.68	78.58%
		Non-suicide	0.85	0.83	0.84	
	AdaBoost	Suicide	0.82	0.81	0.81	87.97%
		Non-suicide	0.91	0.91	0.91	
Twitter	Linear SVC	1	0.77	0.92	0.84	83.69%
		0	0.91	0.77	0.84	
	LR	1	0.78	0.93	0.85	84.83%
		0	0.92	0.78	0.85	
	DT	1	0.77	0.80	0.78	79.36%
		0	0.82	0.79	0.80	
	AdaBoost	1	0.82	0.90	0.86	85.97%
		0	0.90	0.83	0.86	

The essence of findings from Table X indicates a decline in accuracy for most models on the Twitter dataset, however, the F1-score remained consistent for both classes. In contrast, the Reddit dataset, while displaying better accuracy, struggled to identify suicide class. When compared with the results presented in Table V, it is evident that DL models showcased higher competency over ML models.

V. DISCUSSION

Suicide has emerged itself as a global threat to humanity, demanding urgent actions and attentions to address the complex challenges it presents. As early identification of suicidal thoughts is the essential strategy to prevent suicide, our study aimed to detect suicidal tendencies by analyzing social media interactions. Pursuing that, we employed both ML and DL methods and assessed their performance. This study primarily emphasized on DL models while ML models were utilized for comparison. We conducted comprehensive pre-processing and experimented with several word embedding techniques. To verify the outcomes of the models, we utilized multi-source datasets. However, the length restriction of a tweet often proves inadequate for expressing an individual's complex emotions, which might be responsible for the slight performance decline of the models trained on Twitter dataset. We implemented various strategy to examine the generalizability of the models. Despite the notable outcomes of our work, the models possess limitations to assess the risk variables associated with suicide psychology. Pairing our findings with the statistical analysis of the psychologists could make these models a better indicator of suicidal thoughts.

VI. Conclusion

This research aimed to develop and evaluate a detection system to identify suicidal thoughts of individuals by analyzing their social media post. The study intended to reduce suicide rate by detecting suicidal thoughts in the social media interactions of the users. To accomplish this, textual data from Reddit and Twitter was collected and both ML and DL methods was utilized with a view to assess the psychological states of the users. Through meticulous evaluation and comparison of several ML and DL methods, the study has established the commendable predictive accuracy of the proposed model. The proposed model evidently captured the discrepancies of the data in a more effective manner. It evolved into the most proficient model for suicide detection by securing accuracies of 93.07% and 92.47% respectively, on Reddit and Twitter datasets. Subsequently, a manual dataset was created, cross-dataset testing strategy was introduced and cross-validation was performed for further analysis of the generalizing ability of the models. The proposed model showcased superior results in these regards as well. Hence, the hybrid BiGRU-CNN model was proposed as an effective tool for analyzing mental health from social media content to expose suicidal thoughts.

This research concludes by highlighting the proficiencies of the proposed hybrid model and indicating a strong potential for real-world deployment. The insights attained from this study ought to lead the way for future research directions and practical applications. This research contribution is a step forward in the integration of AI into mental health services. It aimed to provide strong foundation for future advancements in NLP and AI-assisted mental health monitoring.

VII. Future Scope

Regardless of promising outcomes demonstrated by the proposed model, there always remains scope for future development. Introducing the proposed model to more diverse data from social media platforms including Facebook and Instagram could significantly enhance the model's understanding, thus accuracy. Additionally, real-world testing through direct integration with social media could provide valuable insights into its reliability and competency in practical applications. Advanced pre-trained transformer models particularly BERT, ELECTRA, and neural networks such as HANN could be employed with a view to compare them against the proposed model. Given the sensitivity of the task at hand, continuous refinement and improvement are crucial to ensure the model's resilience and real-world impact.

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Enhancing the Odia Handwritten Character and Numeral Recognition System's Performance with an Ensemble of Deep Neural Networks

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***Abstract*—Offline handwritten character recognition (OHCR) is considered a challenging task in pattern recognition due to the inter-class similarity and intra-class variations among the symbols present in the alphabet set. In this work, a learning-based weighted average ensemble of deep neural network models (WEnDNN) is proposed to classify the 10 digits and 47 characters present in the alphabet set of Odia language, an official language of India. To build the base model for the ensemble network (EnDNN), three suitable convolutional neural networks (CNN), are designed and trained from scratch. The WEnDNN's accuracy is increased by using a grid search approach to determine the ideal weight allocations to give to the top-performing model. The performance of the WEnDNN model is compared with several standard machine learning models, which take the non-handcrafted features extracted from the finely tuned, pre-trained VGG16 model and a combination of Gabor and pixel intensity values to create handcrafted features. On several benchmark handwritten datasets, including NITR Odia characters (OHCS v1.0), ISI Kolkata Odia numerals, and IITBBS Odia numerals, the performance of the proposed WEnDNN model is assessed and compared. The experimental results demonstrate that, in terms of recognition accuracy, the proposed approach beats other state-of-the-art approaches.**

Keywords—Odia language; ensemble learning; machine learning; Gabor features; CNN; DNN

I. Introduction

It is possible to recognize a symbol easily with our naked eye, but hard for a handwritten character recognition (HCR) model. To reduce this recognition gap between humans and models and to achieve human-like accuracy, handwritten character and numeral recognition (HCNR) systems have made significant advancements in recent years, with various approaches developed in different languages. These systems play a crucial role in applications such as document digitization, automatic form processing, and handwriting analysis. While numerous methods have been proposed to tackle this challenging task, researchers are more inclined towards deep neural networks (DNN). Deep Convolutional Neural Networks have proven their advantage in getting high performance in different applications of pattern recognition tasks when handling large data sets to extract features automatically.

Acquisition of character images, pre-processing, feature extraction, and classification make up the three major steps of the conventional OHCR workflow, and much research in this paradigm has concentrated on enhancing each of these steps. For instance, the feature extraction stage has advanced to the point that many researchers aim to create potent feature descriptors or vectors referred to as handcrafted in the literature. The basic goal of feature engineering is to design features that maximize patterns' separation from other classes while placing patterns from the same class close to one another in the feature space.

From the literature, in the late 1990s, study into the recognition of Odia characters began. The research community has paid a lot of attention to the most popular Indian scripts, Devanagari, Bangla, and Telugu, compared to Odia scripts. Natives of the Indian state of Odisha as well as its neighboring states, including West Bengal, Chhattisgarh, and Jharkhand, are fluent in Odia, a popular and official language of India. The necessity to digitize historical documents available in Odia literature inspires researchers to create Odia HCRs that have advantages for both business and society. The advancement of Odia OHCR needs to be enhanced to meet the requirements of real-time recognition. Modern schemes use features that are manually designed (handcrafted), which requires a lot of work. Several researchers have designed CNN based classification model to obtain deep features (non-handcrafted features) for Odia OHCR [1], [2]. In Odia language, most letters have a perpendicular straight line on the right side, while the upper portions are mostly circular. The characteristics of similar characters present as well as the roundish structure and the randomness of its writing, bring great challenge to the recognition task, which motivates us to propose an Odia OHCR model that enhances the classification accuracy in this regard.

The right selection of feature descriptors still presents the biggest hurdle in these OHCR systems. Utilizing a method known as “transfer learning”, those architectures are being employed for numerous applications all around the world. In this transfer learning method, the weights of a model that has already been trained for a particular job are used for a variety of tasks. Such architectures include VGG16 [3], ResNet, Xception, DenseNet, MobileNet, InceptionNet, ResNeXt etc. These architectures differ from one another in terms of depth, complexity, and size of input data. Despite having been trained on ImageNet 1000 classes, they are successfully used in all applications of pattern recognition tasks. According to Odia OHCR's related work[4], [5], the majority of researchers choose the model that performs better in terms of accuracy in classification. Although significant progress has been made in developing individual handwritten character and numeral recognition models, their accuracy levels often plateau or show diminishing returns with increased complexity. This limitation is primarily due to the inherent variability in handwriting styles, diverse character and numeral shapes, and the presence of noise and distortions in handwritten samples. Therefore, there is a need to explore alternative approaches that can enhance when solving a classical classification problem using various trained machine learning or deep learning models, the model that produces the best results is maintained and the other models are discarded. If all of the trained models are put together for classification, that will be a better option, as some models are good for extracting certain features while some other models are good for extraction of other kinds of features. An ensemble of different trained models can be used for this purpose. In the case of handwritten character recognition using Convolutional Neural Networks (CNNs), an ensemble of different CNNs often performs better than a single CNN for several reasons:

1) Each CNN model in the ensemble is trained independently on a different subset of the data or with different initialization weights. By combining their predictions, the ensemble can help to reduce bias and overfitting.

2) Ensemble learning can help reduce the impact of errors made by individual models. If one model misclassifies a particular handwritten character, other models in the ensemble may still correctly classify it. Through the combination of predictions, the ensemble can reduce the overall error rate and improve the final classification result.

3) Ensemble learning involves averaging the predictions of individual models. This averaging process helps to smooth out noisy predictions and reduce the effects of outliers. By leveraging the collective wisdom of multiple models, the ensemble can provide a more confident and accurate prediction.

4) Different CNN models may excel at capturing different types of features or have different strengths in recognizing certain patterns. By combining the strengths of multiple models, the ensemble can achieve a more comprehensive and discriminative representation of the handwritten characters, leading to improved classification performance.

Now, there is always the option to employ an ensemble learning method that boosts efficiency by using several CNN models for the same tasks. This has inspired researchers that utilize CNNs for the task of character recognition and to develop methods for ensembles of networks to enhance CNN performance. It has been observed from related work that although many efforts have been made in the area of Odia OHCR to improve the performance of the model, no work has presented the ensemble of various CNNs. These models even result in a further improvement in accuracy of about 1 to 2% across the models when combined with the ensemble of different CNN's methodologies outlined in the research. This motivation led us to the development of EnDNN and WEnDNN.

This paper presents a novel approach for offline Odia handwritten character and numeral recognition (OHCNR) by using an ensemble of deep neural networks and a weighted average ensemble of deep neural networks. Our main contributions to this research are as follows:

- Three CNN models are designed from scratch, from a simple to a slightly complex model, by varying the feature maps and number of layers, and these CNNs are combined to create the base model of the ensemble network (EnDNN).
- A grid search method is used to get the right combination of weights to be assigned to the best-performing model to construct a weighted average ensemble of deep neural network models (WEnDNN), to boost the ensemble networks' accuracy.
- Traditional ML models (Random Forest (RF), Support Vector Machine (SVM), k-Nearest Neighbour (kNN), and Extreme Gradient Boosting (XG-Boost) are used, which are trained on non-handcrafted features obtained from fine-tuned, pre-trained VGG16 model and handcrafted features extracted by Gabor filters, combined with pixel intensity values to create feature descriptor.
- The performance of the WEnDNN model is compared with the individual CNN, EnDNN and ML models to show the effectiveness of the proposed work and the models are verified using a set of benchmark Odia databases, namely ISI Image database, NITROHCSv1.0 and IITBBS numeral database.

Here is a summary of the remaining portions of the paper: Some of the most significant studies on deep learning for Odia and other language OHCNR tasks currently published in the literature is highlighted in Section II. Section III discusses the materials and methodology, which covers the description of DCNN models and their components. The datasets used for the proposed work are covered in Section IV and the proposed model architecture is covered in Section V. Section VI reports the results and discussion, and Section VII provides the conclusion.

II. Related Work

In the Odia script, like every other script vowels, consonants, and composite characters (combinations of characters with other characters) are present. A total of 10 numerals and 47 alphabets (vowels and alphabets) are present in the Odia script, as shown in Fig. 3(a), 3(b), and 3(c). With different handwriting styles and high similarity between different characters, it's challenging for any system model to get human-like accuracy. Several works on Odia OHCR were reported in [6], [7] based on handcrafted feature extraction. In [8], authors have used curvature features and reduced the feature set by PCA and with quadratic classifier got a classification accuracy of 94.6%. In [9] Binary External Symmetry Axis Constellation (BESAC), features are used with an accuracy of 95.01 by the k-NN classifier. The authors of

[10] used zone centroid distance and standard deviation to extract features and got 94% accuracy by back propagation NN with a genetic algorithm approach. [11], [12], [13]–[15], [16], [17][18] had contributed their work on handwritten Odia handwritten numeral recognition (Odia OHNR). The same BESAC features are used for numeral classification, on the IITBBS numeral dataset [9]. In [19], the authors achieved an accuracy of 95% by SVM with directional features by zoning method. In a work of [20], authors used Gradient, curvature feature, and Feature reduction using PCA fed to low complexity neural classifier for recognition with an accuracy of 98% by gradient feature and 94% by curvature feature. In [16], the DCT and DWT coefficients are used by the BPNN classifier. Several studies have been reported on the ISI numeral dataset [21][22], [23] with a promising accuracy of over 90% for handwritten Odia numeral recognition.

The goal of researchers is to increase the optical character recognition (OCR) model's accuracy, so they are more focused on deep neural networks and ensembles of networks. To the best of our knowledge, almost little efforts on deep neural networks were contributed to the field of Odia OHCR and OHNR. In [24], the authors proposed RNN and CNN-based classification techniques for Odia compound characters. To improve the classification accuracy, different augmentation techniques were used by [1] to expand the dataset, and different CNNs were used for the classification of Odia handwritten numerals and characters. Different deep learning-based classification models proposed for Bangla OHCR, a sister language of Odia. In [25], the authors used mobilenet v1 architecture, whereas the authors [26] proposed a hybrid Bangla OHCR model that is a combination of stacked Bi-directional Long Short-Term Memory (Bi-LSTM) applied on the features extracted from CNN. A deep analysis was carried out by [27] for Bangla OHCR by different deep networks i.e. InceptionResNetV2, DenseNet121, InceptionNetV3, NASNet, VGG16, VGG19 and authors claimed InceptionResNetV2 as the best performing model. An improved CNN based digit recognition on MNIST dataset with an accuracy of 99.87% by [28].

Combining CNN models into an "ensemble" is one strategy for improving the handwritten character recognition system's accuracy. For the Odia OHCR, very few works based on ensemble networks were published. Three ensemble learning methods (AdaBoost, Bagging, and Random Subspace) are utilized in the study[29], for improved sentiment analysis and in [30]different features were selected and classified using Random Forest, which is an ensemble of several decision trees for Odia vowel recognition. The authors of [31] reported an offline Tai Le OHCR using ensemble deep learning, with a DCNN serving as the primary or base classifier. An ensemble deep learning model is created by stacking several different base classifiers, and the model achieves an accuracy of more than 98% on the Devanagari handwritten characters and MNIST handwritten digits datasets. The base classifiers' parameter combinations are optimized using a grid search technique.

Apart from OCR applications, ensemble networks were used in different fields [23]-[27], and some of the applications are described below. A deep ensemble network by using LSTM-B was proposed by [32] to obtain the accurate results of exchange rates forecasting and to improve the profit of exchange rates trading. The authors of [33] proposed a deep ensemble learning algorithm on a variety of datasets, including those for letter recognition, cancer, diabetes, heart disease, thyroid, etc., which determines the ensemble size, the number of hidden nodes in a neural network, etc. In [34] the authors used CNN as an ensemble model for object detection by selecting the region from each CNN model is combined, classified, and finally voted. Automated audio classification is proposed by [35] that fuses different types of features extracted from audio files and uses different pre-trained CNN models AlexNet, GoogleNet, VGG16, VGG19, ResNet50, InceptionV3 as ensemble and got the maximum accuracy of 99.3% by using ensemble DL and handcrafted features. In [36], the authors used an ensemble model for crash prediction model using road geometric alignments (CPM-GA) with three traditional models NB model and IHSDM-China and IHSDM-US models, and CART+SVM, RF + SVM, CART + BPNN, RF + BPNN as base models of the ensemble by selecting the model by model prediction test and model’s sensitivity test. The results of the ensemble learning CPM-GAs using the IHSDM + China model and CART + SVM model are promising. Due to their improved accuracy, increased robustness, and scalability in model design for character recognition, ensemble models are becoming more and more popular nowadays. Utilizing ensemble data mining techniques for the classification of skin diseases is reported in [42][43]. It explores methods to enhance accuracy and reliability in diagnosing skin conditions through ensemble data mining techniques. To improve optical character recognition (OCR) performance by employing an ensemble of Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), and Extra Trees classifiers is shown in [44]. An ensemble model composed of Convolutional Neural Networks (CNNs) for classifying cloud image patches, particularly on small datasets addresses the challenge of achieving accurate classification results with limited data and is proposed in [45].

III. Materials Used

This section discusses all the materials and methodologies that are utilized to construct the proposed ensemble model of deep neural networks.

A. Deep CNN Models

Due to the non-linear behavior of neural network models, CNNs can learn the complex nonlinear relationships in the given input data. Convolutional layers, pooling layers, and fully connected dense layers are the three fundamental layers that make up the conventional CNN structure. These layers are repeated to make an NN to a deep CNN, and it is shown in Fig. 1.

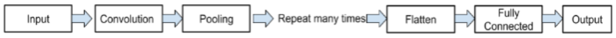


Fig. 1. Basic structure of a deep convolutional neural network.

1) Convolutional layer: These layers identify patterns in images by sliding a filter over the input image to produce a feature space or feature map. If the input image is directly connected to the fully connected layer for classification, we may get the result, but the complexity increases when the input image size is large and the number of images is greater. The expensive computation and the cost reduction can be achieved by including the convolution and pooling layers. The basic convolution operation in convolutional layer is represented mathematically in Eq. (1), where f (x, y) is the input image, c (x, y) is the convolved image and h (x, y) is the filter or kernel.

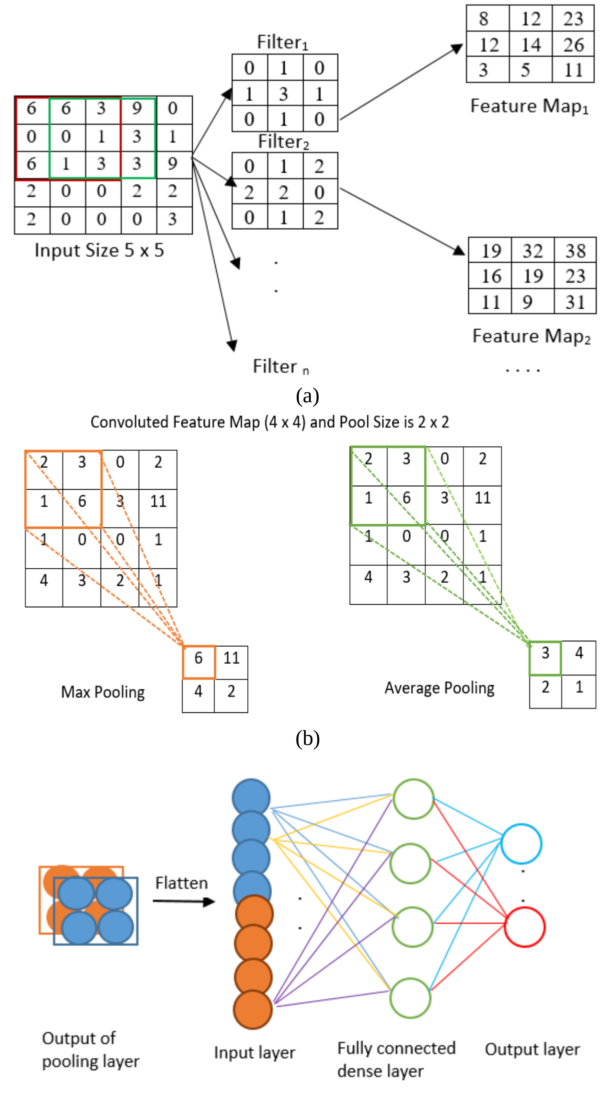
$$\boldsymbol{c}(\boldsymbol{x},\boldsymbol{y}) = \boldsymbol{h}(\boldsymbol{x},\boldsymbol{y}) * \boldsymbol{f}(\boldsymbol{x},\boldsymbol{y}) \qquad (1)$$

The advantage of CNN can be taken to extract important features by reducing the image dimension and keeping important features for better prediction. It learns images by applying a filter of a certain size while maintaining translation invariance, in addition to learning the features from the data. The convolutional layer has several learnable filters, each of which can be thought of as a matrix. The convolutional layer produces numerous feature maps (also known as activation maps), and these feature maps corresponding to distinct filters are layered together along the depth dimension. Each member of the matrix or filter serves as a parameter (weight and bias) of neural networks. The convolutional layer's operational structure is shown in Fig. 2(a).

The basic component of a convolution operation in a convolutional layer is the kernel. The features or significant patterns in an image are extracted from the image using a filter called a kernel. It is a matrix $\boldsymbol{h}(\boldsymbol{x},\boldsymbol{y})$ that traverses the input image $\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})$, performs a dot product with the sub-region of the input data, and produces the matrix $\boldsymbol{c}(\boldsymbol{x},\boldsymbol{y})$ of values from the dot product. To obtain another value in the feature map, the kernel moves the input image by a stride value.

2) Pooling layers: This layer down-samples the features in the feature map by reducing their dimension. It also introduces translation invariance, i.e., even if the CNN input image is translated, the CNN will still be able to recognize the features, which reduces the CNN model's tendency to overfit data. The quantity of network computation and the number of parameters to learn are both decreased by the pooling layer. The two most common pooling methods are max-pooling and average pooling, as shown in Fig. 2(b). The most prominent patterns of the feature map are retained as a result of max pooling, and the resulting image is sharper than the original. Max pooling operates by choosing the maximum value from each pool. By averaging the pool, the average pooling layer operates and it smooths the image by maintaining the image feature's essential qualities.

3) Fully connected dense layer: A dense layer is one whose interior neurons are connected to every neuron in the layer preceding to it. Finally, it is connected with the number of units, the same as the number of classes, and produces output. A CNN model employs one or more FC layers following a series of convolutional, ReLU, or pooling layers to produce the output. The way FC layer works is similar to how classic neural networks work in that it combines all of the features that the earlier layers have acquired in order to find more important patterns. The main issue with the fully connected layer is that it has a lot of trainable parameters and requires a lot of computation to train. Therefore, current research efforts are concentrated on either lowering these layers or substituting methods that may accomplish the same purpose with less computational effort for the layers. A soft-max function is utilized to determine the class label by giving each class a probability distribution after the final FC layer. The operational structure of a fully connected layer is shown in Fig. 2(c).



(a)

(b)

(c)

Fig. 2. (a) The basic operational structure of the convolutional operation. (b) The basic operational structure of pooling. (c) The basic operational structure of fully connected layer.

4) Rectified Linear Unit (ReLU) Activation: After the convolutional layer, the ReLU layer is frequently used, which introduces non-linearity to the output. All negative input values are mapped to zero in this layer, R (I) = max (0, I), and its operation is denoted by the following Eq. (2):

$$\mathrm{R(I)} = \begin{matrix} \mathrm{I} & \text{if } \mathrm{I} \geq 0 \\ 0 & \text{otherwise} \end{matrix} \quad (2)$$

ReLU activation function has several advantages, including computing efficiency, quicker convergence than non-linear functions like sigmoid and tanh, and protection against vanishing gradient issues.

5) Softmax activation: The activation function known as softmax, scales numbers into probabilities that generate a vector V with probabilities for each class. The sum of all output values in the V adds up to 1. It is defined in Eq. (3), where y is the vector of possible outcomes of n elements for n classes, is input to the softmax function and y_j is the j^{th} element of vector y.

$$\mathrm{softmax}(y)_j = \frac{e^{y_j}}{\sum_{k=1}^{n} e^{y_k}} \quad (3)$$

6) Cross-entropy as loss function: The cross-entropy loss quantifies the dissimilarity between the predicted class probabilities and the actual class labels. It penalizes the model for assigning low probabilities to the correct class and assigning high probabilities to incorrect classes. The loss value is larger when the model's predicted probabilities deviate further from the true expected values. During the training process, the model's weights are adjusted to minimize the cross-entropy loss. By iteratively updating the weights using techniques like gradient descent, the model learns to improve its predictions and reduce the loss. As the model gets better at classifying the handwritten characters, the loss decreases. Cross entropy is defined in Eq. (4), where t_j is the true label and p_j is the class probability value computed by the softmax activation function for class j.

$$CE = -\sum_{j=1}^{n} t_j \log(p_j) \quad (4)$$

IV. Databases

A benchmark database is necessary for any text recognition research to be successful. For efficient classifier or recognizer training, large databases are needed. The accuracy of recognition is entirely dependent on the type of feature extractor employed and the number of training samples taken from the database because of cursive scripts and various handwriting styles. The databases used for our study are shown in Table I, and sample images from the databases are shown in Fig. 3. The NITROHCSv1.0 data set is publicly available on the NIT Rourkela website, IITBBS numeral, and ISI image database will be available on request. These three databases are only available to the research community on the handwritten character recognition of the Odia language.

TABLE I. Handwritten Odia Character and Numeral Datasets

Database	Training Size	Testing Size
ISI Image Database	4,970	1,000
IITBBS Numeral Database	4,000	1,000
NITROHCSv1.0	10,528	4,512

1) ISI image database: An isolated database of handwritten Odia numerals was created in 2005 by [37] at ISI Kolkata, India. There were precisely 356 participants in the data collection procedure. It has 5,970 samples that were gathered via 166 application forms, and 105 pieces of mail, and the remaining samples were personally collected. The data set is then split into a training set and a test set, consisting of 4,970 samples and 1,000 samples, respectively. Sample numeral images of the ISI Image Database are shown in Fig. 3(a).

2) IITBBS numeral database: A new database for Odia numerals has been discussed by the authors [38] at the IIT in Bhubaneswar. At 300 and 600 dpi, the images were scanned. The IITBBS numeral database now has 5,000 handwritten examples of Odia numbers, and the database contains 10 classes and the sample numeral images are displayed in Fig. 3(b).

3) NITR OHCSv1.0 character database: Databases are also created and defined at NIT Rourkela by [39], which contains an Odia alphabet with 47 classes. There are 15,040 samples of atomic characters from the Odia language in the OHCSv1.0 database, each class contains 320 images. Data collection, picture enhancement, and size normalization are the procedures used in the construction of the database using the Odia character set. The database is split into 70:30 ratios for train and test sets. The total number of images in the train and test set is 10,528 and 4,512. Fig. 3(a) represents Odia character images of the NITR OHCSv1.0 database.

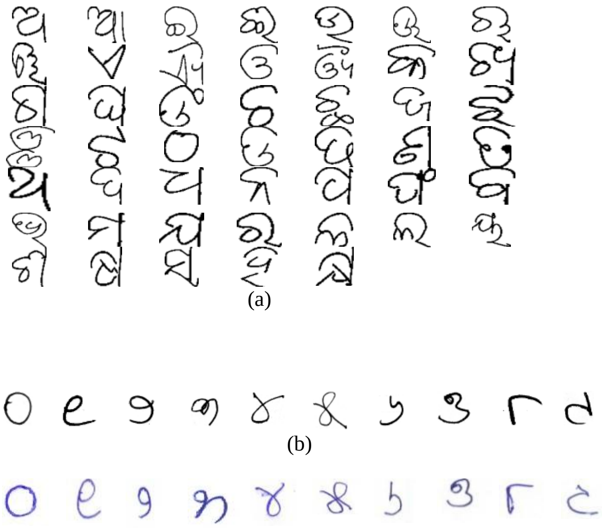


Fig. 3. (a) Sample characters of NITROHCSv1.0 database. (b) Sample numerals of ISI Image numeral database. (c) Sample numerals of IITBBS numeral database.

V. Methodology

The following are the steps of the experimental environment for the Odia handwritten character and numeral recognition model (OHCNR), which is shown in Fig. 4.

- Load handwritten images from the training and test sets.

- Convert the images to grayscale.
- Normalize the pixel values of the grayscale images to a range of 0 to 1. This enhances the training of the neural network (NN) model.
- Design three CNNs as base models for the Ensemble Deep Neural Network (EnDNN).
- Construct the EnDNN by integrating the three designed CNNs.

Select the right combination of weights by the grid search method to be assigned to the best-performing model to construct WEnDNN.

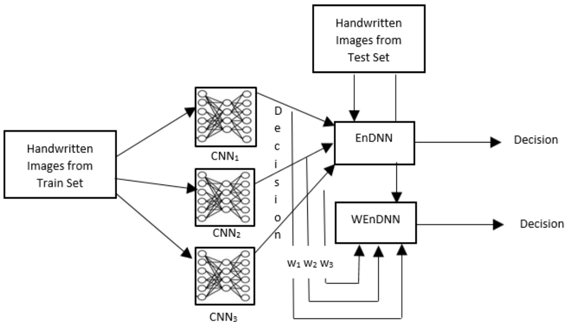

Handwritten Images from Test Set
Handwritten Images from Train Set
CNN₁
CNN₂
CNN₃
D e c i s i o n
EnDNN
Decision
WEnDNN
Decision
W₁ W₂ W₃

Fig. 4. Proposed OHCNR model.

1) Designed CNN models as base model for EnDNN: To achieve high recognition accuracy, a character and numeral classifier based on a convolutional neural network (CNN) is used. Convolutional, max-pooling, fully-connected, and softmax layers are used in the construction of three different CNN-based handwritten digit classifiers. Additionally, the training is carried out utilizing the back-propagation method with mini-batches of size 28 and the adam optimization methodology. When an image is processed for a character recognition task, the crucial features are retained in the convolution layers, intensified, and maintained throughout the network, while the irrelevant information is eliminated by the pooling operation. Fig. 5 lists the parameters utilized in all three created CNN classifiers, each of which has a distinct number of convolutional layers, kernel sizes, filters, and strides.

For instance, the CNN1 depicted in Fig. 5(a) contains one output layers of 10 classes, 2 max pooling layers, 3 convolutional layers, and 1 fully-connected layers. The size of kernel, stride value, and number of filters in the first convolutional layer are 3 x 3, 1, and 32 with an activation function ReLU. For down sampling, pool of size (2,2) is applied in max-pooling layer, next to convolutional layer to reduce the dimensions with a dropout value of 20%. The second convolutional layer of filter size (3,3) and 64 number of filters are used with a dropout value of 20%. 128 filters with a (3,3) filter size are put in the third layer. Next the feature map is flattened to create one dimensional feature vector and one fully-connected dense layers are used, which are connected with 10 output classes. To calculate the class probabilities for three CNN models, ReLU activation function is utilized in the hidden layer and softmax activation function is used in the output layer. Categorical cross entropy is used as the loss function, and iteratively updating network weights based on training data is done using the adaptive moment estimation (adam) optimization method. The input images are fed to the network taking 28 images as a batch at a time and epoch size is 10. In Fig. 5(b) and 5(c), the other two classifiers' convolutional, max pooling, and fully connected layer counts with activation functions are displayed.

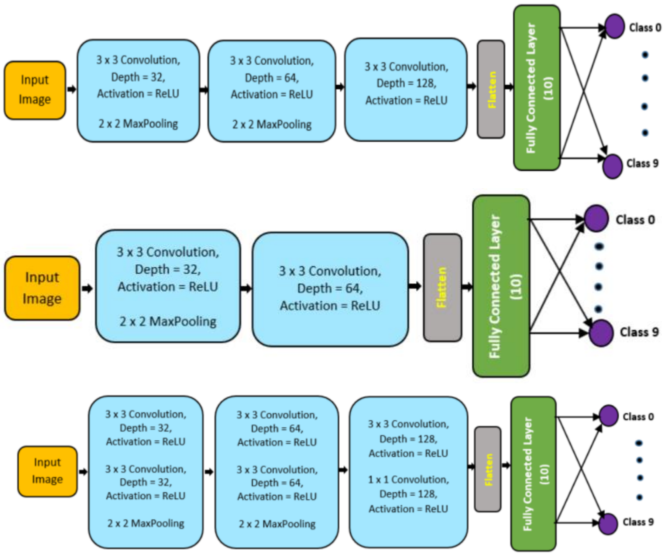

Input Image
3 x 3 Convolution, Depth = 32, Activation = ReLU
2 x 2 MaxPooling
3 x 3 Convolution, Depth = 64, Activation = ReLU
2 x 2 MaxPooling
3 x 3 Convolution, Depth = 128, Activation = ReLU
Flatten
Fully Connected Layer (10)
Class 0
Class 9
Input Image
3 x 3 Convolution, Depth = 32, Activation = ReLU
2 x 2 MaxPooling
3 x 3 Convolution, Depth = 64, Activation = ReLU
Flatten
Fully Connected Layer (10)
Class 0
Class 9
Input Image
3 x 3 Convolution, Depth = 32, Activation = ReLU
3 x 3 Convolution, Depth = 32, Activation = ReLU
2 x 2 MaxPooling
3 x 3 Convolution, Depth = 64, Activation = ReLU
3 x 3 Convolution, Depth = 64, Activation = ReLU
2 x 2 MaxPooling
3 x 3 Convolution, Depth = 128, Activation = ReLU
1 x 1 Convolution, Depth = 128, Activation = ReLU
Flatten
Fully Connected Layer (10)
Class 0
Class 9

Fig. 5. (a) CNN1 architecture. (b) CNN2 architecture. (c) CNN3 architecture.

a) Steps of the recognition process by CNN: The handwritten characters and numeral recognition process, using a Convolutional Neural Network (CNN), typically involves the following steps:

i) Data Acquisition: Collect Odia handwritten dataset

ii) Data Split: Creating training and test sets from the dataset. The model is trained using the training set, and its performance is assessed using the test set.

iii) Pre-processing: Applying pre-processing techniques to the images in both the training and test datasets like resizing the images to a consistent size, applying image enhancement techniques, and normalization.

iv) Data Normalization: Normalizing the pixel values of the images so that they range from 0 to 1. This step helps in improving the convergence of the neural network during training and ensures that all features have a similar scale.

v) Batch Training: Dividing the training dataset into batches of a suitable size. Batch training involves feeding a subset of the training data to the network at a time instead of using the entire dataset in one go. This approach facilitates efficient computation and allows the network to update its weights based on smaller subsets of data at each iteration.

vi) Model Training: Training the CNN model and its variants using the labelled training data. This step involves feeding the batches of training images to the network, performing forward and backward propagation, and adjusting the network's weights using optimization techniques like gradient descent. The training process aims to minimize the difference between the predicted output and the actual labels.

vii) Classification: Using a trained model to classify new, unseen images. This involves passing the test images through the trained network and obtaining predictions for each image. The predicted labels are compared to the true labels to evaluate the model's accuracy.

viii) Performance Analysis: Analysing the recognition accuracy and processing time for all the variants of the trained model. This step includes calculating metrics such as accuracy, precision, recall, and F1 score to assess the model's performance. Processing time can be measured during both training and classification phases to evaluate the efficiency of different model architectures and training strategies.

2) Ensemble of Deep Neural Networks (EnDNN): Ensemble is the process of combining several learning algorithms to improve the performance of existing models by combining different models into a single reliable model. There is now always the choice to use an ensemble learning approach, which increases efficiency by applying a number of CNN models to the same tasks. By training numerous models instead of just one and combining their predictions, neural network models can successfully reduce their variance. So, the ensemble learning method, not only lowers the variance of predictions but also has the potential to produce predictions that are superior to those produced by a single model.

In a CNN, the produced output probabilities are o1, o2, o3 .. on, where $\sum o_i = 1$, for an unseen image x of n-class classification, the CNN determines the unseen image x belongs to the class i with the greatest likelihood probability oi. In our study, the proposed CNNs should provide a probability value to each unseen test image that it was labelled by either of the 10 numerals for numeral recognition or 47-character classes for character recognition. Class probabilities for each image, derived by the individual CNN's, will be the input of our ensemble of networks and the ensemble algorithm is shown in Algorithm 1. Every individual model will make a prediction based on the test data. The ensemble approach combines the predictions of the three CNN models by summing their predicted probabilities and selecting the class with the highest summed probability as the final prediction.

Algorithm 1: EnDNN: The algorithm evaluates the performance of three designed CNN models individually and an ensemble of the three models by comparing their predicted labels with the true labels.

```
1. Load the dataset of Odia character or numeral images along
   with their corresponding class labels.
2. For each image in the dataset:
       • Apply pre-processing techniques such as
         resizing, RGB to Gray conversion and
         normalization.
3. Define three sets of convolutional neural network (CNN)
   models as the base models for the ensemble. (The
   architecture of each model is defined in Section 5)
4. Split the pre-processed dataset into training and test sets.
       • For each base model in the ensemble:
           ▪ Train the model on the training set using adam
             as an optimizer and categorical – cross entropy
             to compute loss.
           ▪ Evaluate the model's performance on the test
             set to measure its individual recognition
             accuracy.
           ▪ Save these models as CNN1, CNN2, CNN3.
5. Load these pre-trained models: CNN1, CNN2, CNN3.
6. For each model in the list of models, do the following:
       • Predict the output for the test data and store the
         predictions in the prediction list.
7. Sum the prediction probabilities of each test image for each
   class obtained from different models of ensemble DNNs.
8. Determine each test image's maximum class recognition
   accuracy from the summed prediction values of an
   ensemble of DNN as ensemble accuracy:
       • For each test image in the dataset:
           ▪ Determine the class or category with the highest
             summed prediction value.
           ▪ Compare this prediction with the ground truth label
             of the image.
           ▪ Calculate the ensemble accuracy by measuring the
             percentage of correctly recognized test images
```

3) Weighted ensemble of DNNs (WEnDNN): Since deep learning models differ in architecture and complexity, not all of them produce the same outputs; some produce superior output than others. To get the maximum output from any model, it would be beneficial if we gave larger weights to the better-performing models. Weighted ensemble learning is a variation of ensemble learning where different models in the ensemble are assigned different weights to determine their contribution to the final prediction. In the case of handwritten character recognition using a weighted ensemble of different CNNs, it can perform better because assigning different weights to individual CNN models allows the ensemble to emphasize the strengths of each model. Certain CNN models may be particularly effective at recognizing specific types of handwritten characters or capturing certain features. Models that consistently produce more accurate predictions can be assigned higher weights, while models with lower accuracy can be assigned lower weights. By assigning higher weights to these specialized models, the ensemble can benefit from their expertise and improve the classification accuracy for the corresponding classes.

Finding the ideal mixture of model weights is the issue in this situation, and the grid search method is employed to achieve this. To determine the best weight, various weight combinations were tested. The search procedure will continue until it has checked every combination, at which point the algorithm will give us the ideal weight combination that maximizes accuracy. We multiply the output probability values $output_{ij}$ of CNN_j (i =1,2 and 3) by $\omega eight_j$ (j = 1,2, and 3) after determining the appropriate weights for all the individual CNNs, and the class probabilities are calculatedwe using the weighted output probability values $\omega eight_j output_{ij}$ instead of the original output$_{ij}$ ones. The weighted ensemble algorithm is shown in Algorithm 2.

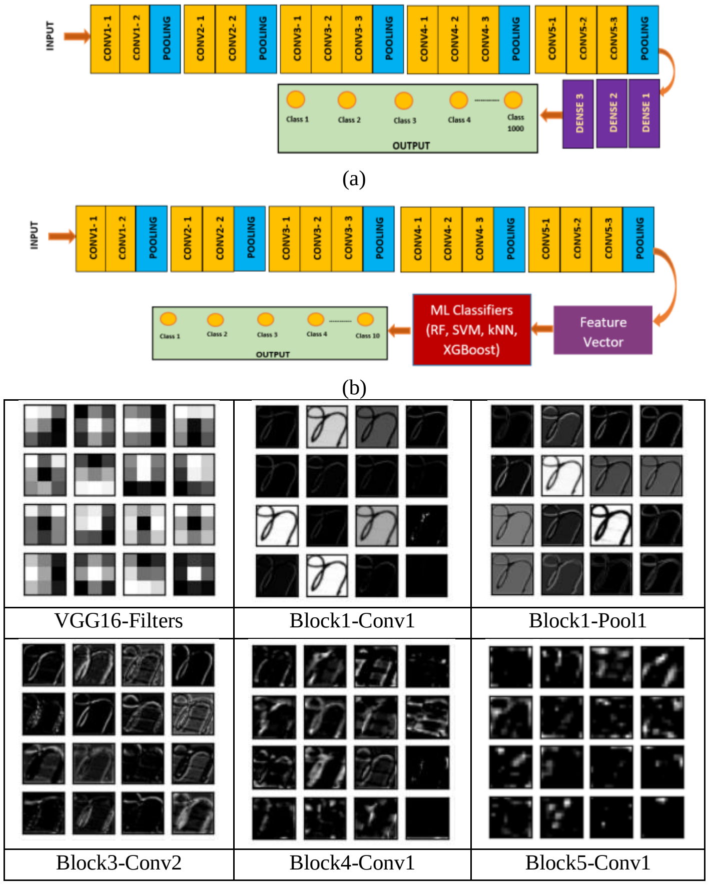
Algorithm 2: WEnDNN: This algorithm outlines the steps involved in generating predictions using an ensemble of DNNs with different weighting schemes and evaluating the accuracy of the weighted ensemble predictions on the test data.

1. Create a list for an ensemble of models, called models, and add the models (CNN1, CNN2, and CNN3) to it.
2. Initialize equal weights for each base model in the ensemble.
3. For each model in models, do the following:
   - Predict the output for each image in test set and store the predictions in the predictions list, where each base model’s prediction should be weighted equally at the start.
     predictions ← [prediction1, prediction2, prediction3]
4. Generate different combinations of weights for the base models in the ensemble.
   weights ← [weight1, weight2, weight3]
5. For each possible weight combination, multiply each prediction by its corresponding weight.
   weighted_predictions ← *prediction$_i$* * *weight$_i$*, where i = 1,2,3
6. For each test data instance, determine the weighted ensemble prediction by selecting the maximum value among the weighted predictions.
   - Combine the predictions from different models and choose the prediction with the highest weighted value. *weighted_ensemble_prediction←maximum (weighted_prediction)*
7. Compare the weighted ensemble predictions to the ground truth labels of the test data.
   - Calculate the accuracy of the weighted ensemble by measuring the percentage of correctly predicted instances.

4) OHCNR model with deep and hand-crafted features: In order to evaluate the performance of the proposed OHCNR model, two more experiments were carried out by extracting deep features using a pre-trained VGG16 model and handcrafted features from Gabor filter that captures texture features and pixel-level features from the images and use these features to train and test machine learning models for recognition purpose.

a) Extraction of deep features from pre-trained VGG16 model: The researchers use a variety of strategies to extract the pertinent features, whether handcrafted or non-handcrafted. Automatic feature extraction techniques have grown in popularity in recent years for solving character recognition problems due to their capacity to extract robust features. For non-handcrafted feature extraction, transfer learning techniques have recently been applied. A learned model for one problem is used for solving another problem, a process known as transfer learning. Diverse pre-trained models, including VGG16 (Visual Geometry Group), VGG19, InceptionV3, MobileNetV2, Resnet50, ResNetV2, Xception, DenseNet, etc., are used in transfer learning. The weights of the pre-trained models are used for the training process for the new problem. These pre-trained models are used for classification tasks, stand-alone or integrated feature extraction processes, and weight initialization. These non-handcrafted features are fed to RF, SVM, kNN, and XG Boost to train these models and compare the results with the proposed state-of-the-art model.

Data from a subset of the ImageNet dataset, which consists of over 14 million photos organized into 22,000 classes, was used to train a DCNN variation called VGG16 [3]. The VGG16 Model has 16 convolutional layers and, 5 max pooling layers connected to convolutional layers of 5 different blocks, 3 dense layers for the fully-connected layer, and an output layer with 1,000 nodes. The model architecture of VGG16 is shown in Fig. 6(a). To extract the deep features from the handwritten character image can be possible by removing the last few layers (fully connected layers) from the VGG16 model, as they are specific to classification, and retaining the convolutional layers, and its architecture is shown in Fig. 6(b). The filters of size (3,3) is used at different layers to extract deep features automatically. The filters and extracted features after layers Block1-Conv1, Block1-Pool, Block3-Conv2, Block4-Conv1 and Block5-Conv1 by VGG16 model for the Odia digit 3 is shown in Fig. 6(c).



(a)

(b)

(c)

Fig. 6. (a) VGG16 Model architecture. (b) Deep feature extraction from VGG16 model. (c) Extracted features at different layers of VGG16 model.

b) Extraction of hand-crafted features using Gabor filter bank, pixel intensity values: According to the literature, the feature extraction stage of OCR is the one that most heavily influences any system's accuracy among all other OCR stages. Different hand-crafted features that can be extracted from an image are structural or geometrical features. Either the entire image or the features that were taken from it serve as the input to any OCR. An image is made up of high-frequency components that originate from the edges, or the sudden changes in intensity values, and low-frequency components that make up the image's smooth sections. Any image must be transformed into a specific domain to be analyzed. In [40], to extract the discriminant features from a picture, image transformation is an essential step. Gabor filters are typically employed in texture analysis, edge detection, feature extraction, and other aspects of image processing and computer vision since they are independent of light, rotation, scale, and translation. They also infer optimal localization, making them a strong candidate for feature extraction issues.

In our study, 2D Gabor filter bank [41] is used. It is a sinusoidal plane with a certain frequency and orientation that is modulated by a Gaussian envelope is known as a 2D Gabor filter. The Gaussian component provides the weight, and the sine component provides the directionality. By using the Gabor filter, a bank of filters that can be used to detect and extract textures present in an image are created. The Gabor filter has a real and an imaginary component, as shown in Eq. (5), (6), and (7).

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(-\frac{x'^2 + y'^2}{2\sigma^2}\right) exp\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \quad (5)$$

The real part and imaginary parts are represented as:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(-\frac{x'^2 + y'^2}{2\sigma^2}\right) cos\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \quad (6)$$

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(-\frac{x'^2 + y'^2}{2\sigma^2}\right) sin\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \quad (7)$$

Where,

$$x' = xcos\theta + ysin\theta \ and \ y' = -xsin\theta + ycos\theta$$

The parameters are (x, y) is size of the kernel, σ is the standard deviation or sigma of the Gaussian envelope, ψ is the phase offset, θ is the orientation of the Gabor function, γ is spatial aspect ratio and λ is the wavelength of sinusoidal component. These five parameters determine the magnitude and shape of the Gabor function shown in Table II. By adjusting these parameters, a variety of Gabor filters can be applied to extract relevant characteristics from an image.

In our study, a bank of Gabor filters with a constant frequency for various standard deviations (1.5, 2, 2.5) and orientation values ($\frac{\pi}{4}$, $\frac{\pi}{2}$, $\frac{3\pi}{4}$), are created to extract features. For every handwritten image, nine Gabor filters (GF) are created which are convoluted on original image to get the filtered image. The largest response occurs at edges and locations where texture changes when a Gabor filter is applied to an image. Also, the pixel intensity values are included to the handcrafted feature descriptor (HFD) as shown below:

$$HFD = Pixel_{value}, GF_1, GF_2, GF_3, GF_4, GF_5, GF_6, GF_7, GF_8, GF_9$$

The sample two numeral images (0, 3) and character images (ma, pa) and their transformation following the application of the filter are shown in Fig. 7.

TABLE II. GABOR KERNEL PARAMETERS

Gabor Kernel Parameters	Purpose
Sigma (σ)	Determines the total size of the Gabor envelope. The envelope grows to allow more stripes when the bandwidth is bigger, and it shrinks when the bandwidth is smaller.
Aspect ratio (γ)	Determines the height of the Gabor function, height increases at very low gamma values and falls at very high aspect ratios.
Theta (θ)	Determines the Gabor function's orientation. Theta at $\frac{\pi}{2}$ and 0 degree represents the horizontal and vertical positions of the Gabor function.
Wavelength (λ)	It controls the strips' width. When the wavelength is lowered, stripes are thinner; when the wavelength is increased, stripes are thicker.
Phase offset (ψ)	Varying the phase offset can help in detecting edges or texture patterns in different orientations and locations within an image.

c) Classification by machine learning algorithms: Utilizing the Support Vector Machine (SVM), Random Forest (RF), XG Boost, and k-Nearest Neighbor (kNN) algorithms, the performance of the proposed OHCNR model is compared with these techniques.

i) Random Forest: Random Forest is a bunch of decision trees (DT), a supervised learning methodology that can be applied to classification problems based on the idea of ensemble learning (EL). The method of integrating various classifiers to address complex problems and improve model performance is known as EL. Random forest takes a random subset from the training dataset, and adds some duplicate instances to make the same size as the training set. This is called a bootstrapped dataset, and its working procedure is shown in Fig. 8(a). So many DT's are trained on these various subsets of the training set, and it takes the average value to make the decision. Instead of depending on a single decision tree, the random forest uses decisions from all of the trees to anticipate the outcome based on majority voting. The root of RF takes a random subset of features available and picks the one that gives the best split in data based on Gini impurity, as shown in Eq. (8), where C is the number of classes and p(i) is the probability of randomly picking an element of class i.

$$G = \sum_{i=1}^{C} p(i) + (1 - p(i)) \quad (8)$$

ii) Support Vector Machine: A supervised machine learning technique called SVM requires labelled data. The goal of the SVM algorithm is to find the best decision boundary or line that divides the data into "n" classes so that following data points can be promptly classified into the appropriate class category. This ideal decision boundary is known as the "hyperplane". Mathematically, any hyperplane can be represented as in Eq. (9), where xi is the feature value.

$$\sum_{i=1}^{k} w_i . x_i + b = 0 \quad (9)$$

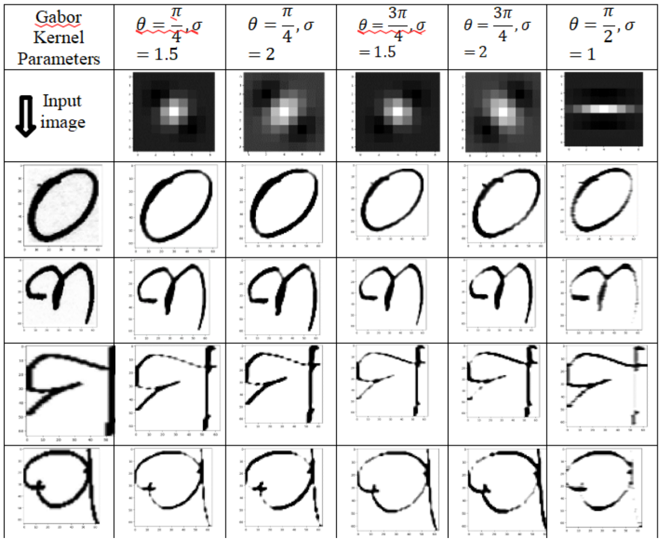
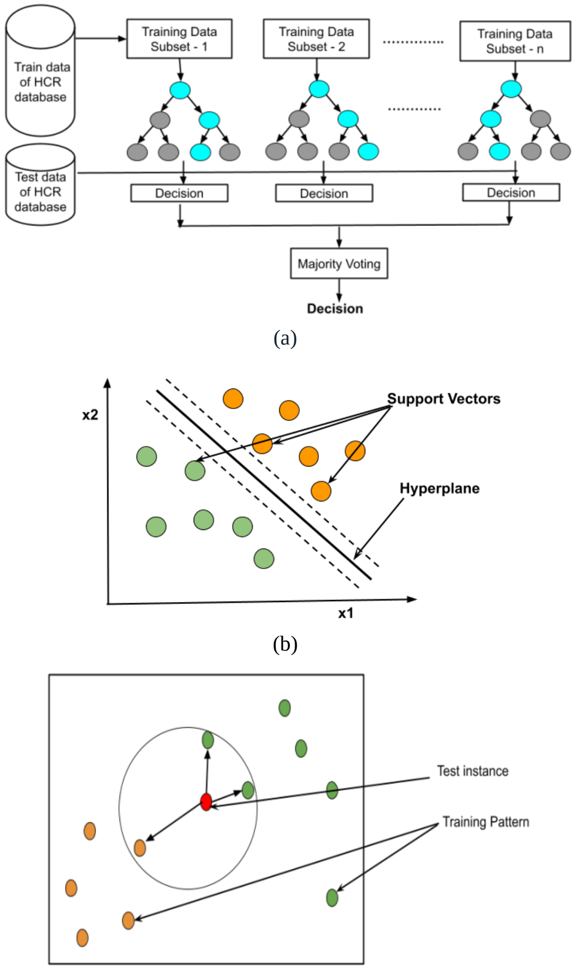

Gabor Kernel Parameters
$\theta = \frac{\pi}{4}, \sigma = 1.5$
$\theta = \frac{\pi}{4}, \sigma = 2$
$\theta = \frac{3\pi}{4}, \sigma = 1.5$
$\theta = \frac{3\pi}{4}, \sigma = 2$
$\theta = \frac{\pi}{2}, \sigma = 1$
Input image

Fig. 7. Input, Gabor filter and filtered image.



(a)

(b)

(c)

Fig. 8. (a) Working procedure of random forest. (b) Working procedure of support vector machine. (c) Working procedure of k – Nearest neighbor.

Support vectors are the data points or vectors that are closest to the hyperplane and have the biggest impact on where the hyperplane is located, as seen in Fig. 8(b).

iii) Extreme Gradient Boosting (XG Boost): Gradient boosting is the technique of "boosting" or strengthening a single weak model by combining it with a number of additional weak models to produce a more reliable model all together. The XG Boost is a gradient boosting solution that pushes the limits of processing power for boosted tree algorithms. It is scalable and incredibly accurate. It was developed mainly to improve the efficiency and performance of machine learning models. In addition to building trees, XG Boost also evaluates the quality of splits at each potential split in the training set by scanning through gradient values level-wise and using these partial sums.

iv) K-Nearest Neighbor (kNN): One of the fundamental classification algorithms, the k-nearest neighbor algorithm, is well-liked for its effectiveness and simplicity. It stores the training dataset rather than learning from it immediately, which makes it a lazy learner algorithm. The algorithm selects k, the number of the nearest data points or neighbors, then calculates the Euclidean distance of the k number of neighbors, and its working process is shown in Fig. 8(c). The most popular classes are selected and given to the test pattern in the k-NN algorithm after searching for the closest training patterns for each test pattern. Some of the method's limitations are that it stores the complete training set for testing purposes, searches the entire training set in order to categorize a certain pattern, and that classification performance suffers in the presence of noisy data.

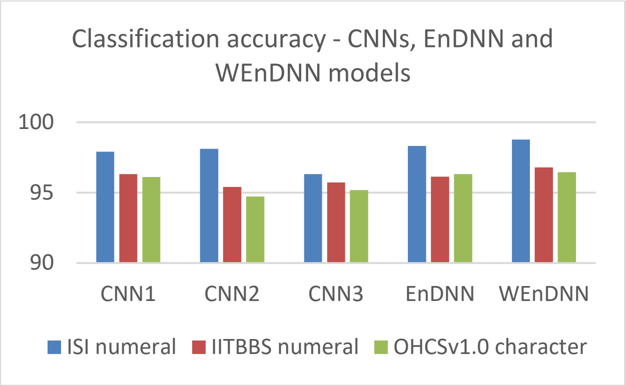
VI. Result Analysis

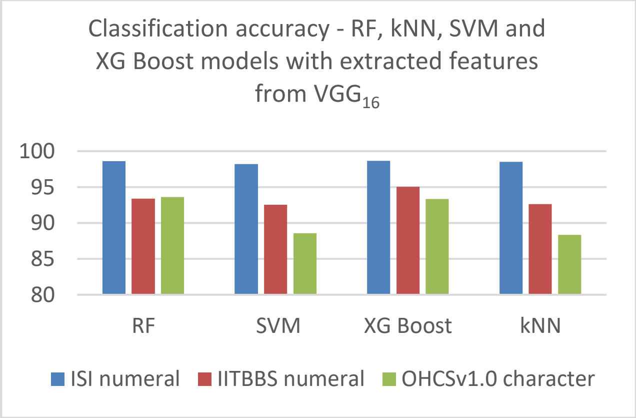
A PC with a 2.81 GHz processor and 16 GB of RAM was used to implement both the proposed character recognition model and the state-of-the-art models. The EnDNN model is implemented in Python to evaluate its recognition accuracy of handwritten characters and numerals. Training and validation accuracy are computed for the three different CNN, EnDNN, and WEnDNN models. Three standard benchmark datasets of handwritten Odia characters are used to evaluate the performance of the proposed model. Table I lists the number of samples used in training and testing for each dataset. The accuracy is calculated by using a confusion matrix and is defined as the number of correct predictions by the classifier based on the total number of predictions. For our study, in a random forest model, 50 decision trees are ensembled. The handcrafted features for our study were a combination of pixel intensity values (PV) as well as features extracted from Gabor filters (GF). The Gabor filters are applied to original images with the following parameters: Image size (x, y) = (9,9) $\sigma = 1.5,\ 2,\ 2.5$ $\theta = 45^0, 90^0, 135^0, \lambda = 0.79$, $\gamma = 0.5$ and $\psi = 0$. The classification result obtained from different experiments by these models with handcrafted and non-handcrafted feature descriptors is shown in Table III.

TABLE III. PERFORMANCE ANALYSIS OF THE PROPOSED MODEL

Approach	**Descriptor**	**Datasets**		
		ISI Image – numeral (10 classes)	**IITBBS-numeral (10 classes)**	**NITROHCS – character (47 classes)**
1. Handcrafted features with ML algorithms	Pixel value +Gabor + RF	95.80	90.34	91.93
	Pixel value + Gabor + SVM	94.81	89.52	90.62
	Pixel value +Gabor + XG Boost	94.21	91.21	90.01
	Pixel value +Gabor + kNN	92.51	88.78	89.85
2.Non-handcrafted feature with VGG16 + ML algorithms	VGG$_{16}$ + RF	98.61	93.37	93.59
	VGG$_{16}$ + SVM	98.21	92.54	88.58
	VGG$_{16}$ + XG Boost	98.67	95.03	93.35
	VGG$_{16}$ + k NN	98.50	92.63	88.36
3.Non-handcrafted feature with NN	CNN$_1$	97.92	96.31	96.11
	CNN$_2$	98.12	95.40	94.73
	CNN$_3$	96.33	95.73	95.19
4.Ensemble of Deep learning models	EnDNN	98.33	96.13	96.31
5.Weighted Ensemble of Deep learning models	WEnDNN	98.78	96.81	96.45

Table III and Fig. 9 investigate the performance of the WEnDNN model under different datasets. The proposed state-of-the-art model's performance was also compared with other approaches (1-5). The experimental results highlighted that the proposed WEnDNN model has gained maximum recognition performance for all handwritten characters as well as numeral recognition. This is because each model in the ensemble might focus on different aspects of the input data, capturing distinct patterns and characteristics of handwritten characters. Each CNN model in an ensemble learns different representations or features from the input data. Combining these diverse representations allows the ensemble to capture a broader range of patterns and variations in handwritten characters. By combining the strengths of multiple models, the ensemble can achieve a more comprehensive and discriminative representation of the handwritten characters, leading to improved classification performance in EnDNN. In case of WEnDNN, the weights assigned to CNN models can be dynamically adjusted based on their performance on validation data or during training. By continuously adjusting the weights, the WEnDNN optimizes its performance, leading to improved classification accuracy.





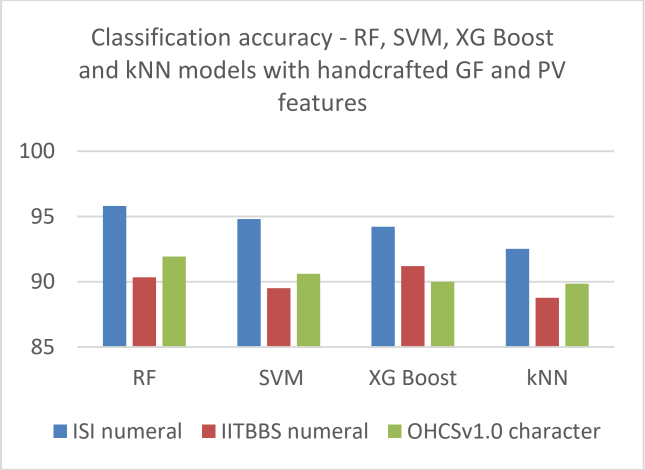


Fig. 9. Result analysis of proposed ensemble model and different ML models with hand-crafted and non-handcrafted features.

The training and validation accuracy as well as training and validation loss of CNN1, CNN2, and CNN3 for the ISI image database are shown in Fig. 11. The confusion matrix and fraction of incorrect predictions of the proposed WEnDNN for the ISI Image numeral database are shown in Fig. 12(a). Structural difference between the numerals present in Odia language is shown in Fig. 10, which leads to more misclassification results. From Fig. 12(b), it is clear that the incorrect prediction of the numeral six(୬) is more compared to other numerals, as six(୬) is predicted as nine (୯), three(୩) or seven(୭).

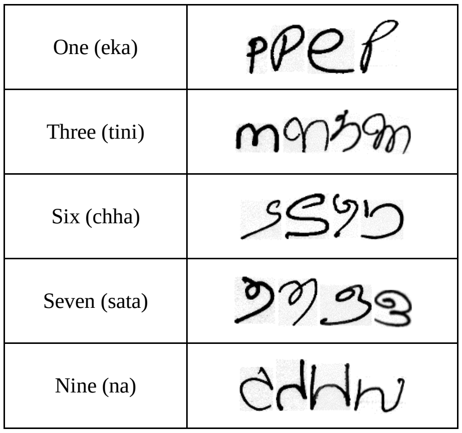


Fig. 10. Structurally different numerals in ISI Kolkata Image database.

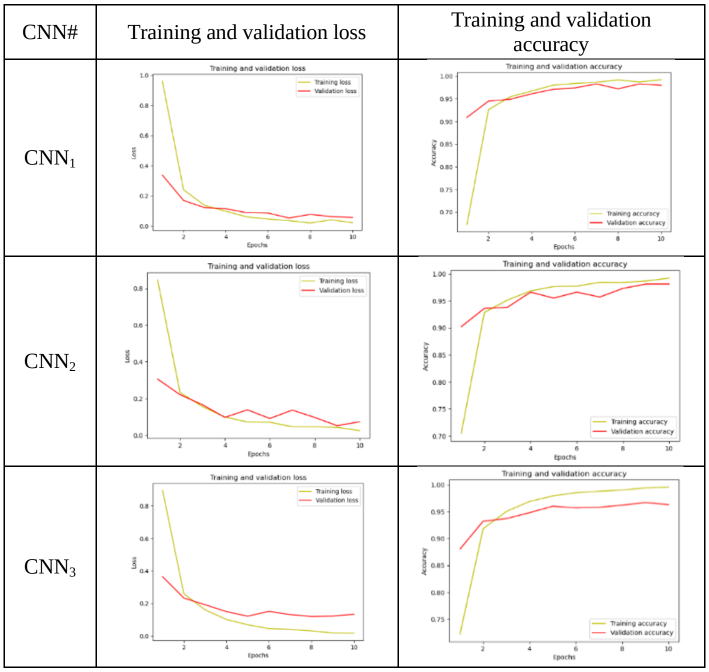
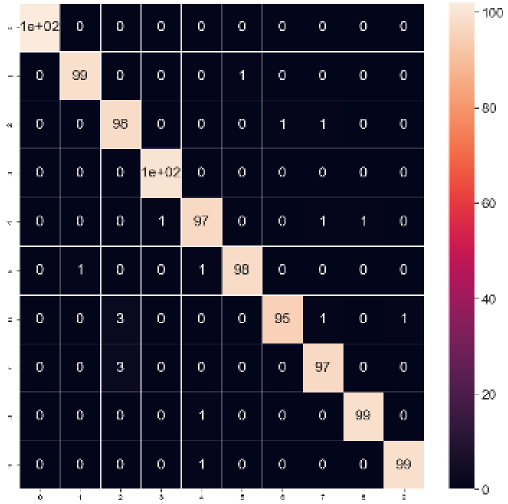
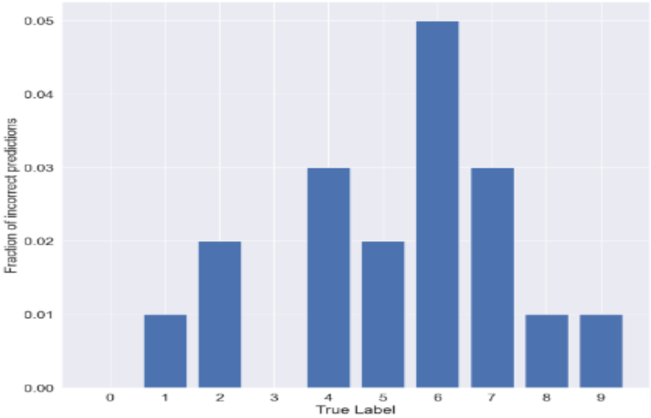


Fig. 11. The training and validation accuracy and loss at each epoch of ISI numeral database.



(a)



(b)

Fig. 12. (a) Confusion matrix of WEnDNN. (b) Fraction of incorrect predictions of WEnDNN.

WEnDNN can also handle the noise in a more effective way. When noise is present in the data, different models may have different levels of sensitivity to noise. By combining their predictions with appropriate weights, the ensemble can reduce the impact of noise by relying more on the predictions of models that are less affected by the noise. If a particular CNN model is more susceptible to noise and tends to produce incorrect predictions for noisy samples, its weight can be reduced. Other models that are more accurate in the presence of noise can be assigned higher weights. By giving more importance to the predictions of robust models, the ensemble can mitigate the effects of noise and make more reliable classifications.

A comparison among the performance of ensemble model applied on applications is shown in Table IV.

TABLE IV. DIFFERENT ENSEMBLE LEARNING APPLICATIONS

Reference	Application field	Method	# of classes	Accuracy
[42]	skin disease	Ensemble CART, SVM, DT, RF, GBDT	6	95.9%
[43]	skin disease	Ensemble using Bagging, AdaBoost and Gradient Boosting classifier techniques; PAC, LDA, RNC, BNB, NB, ETC	6	98.56% - Bagging 99.25% - AdaBoost 99.68% - Gradient Boosting
[44]	OCR	Ensemble of Decision Trees, Random Forest, Extra Trees Classifier, MLP, and SVM for the detection of printed regions in an invoice	-	94.53%
[31]	OCR	Ensemble of 30 deep convolutional neural network model was constructed using a stacking method	35	98.85%
[45]	Cloud image patches	Ensemble of 10 CNN’s (4 CONV	5	99.40%

		and POOL layers and 3FC layers)		
[46]	IoT Cyber Attacks	An Ensemble of Deep RNN for the detection of IoT Cyber Attacks by 6 LSTM models	2	99.41%
[47]	Cardiovascular Disease	An ensemble-based approach of machine learning and deep learning models	2	88.70%
[48]	Plant disease	An ensemble of Random Forest and K-Nearest Neighbor (KNN)	3	96.00%

VII. CONCLUSION

This study makes an effort to identify the handwritten atomic Odia character and numeral. The handwritten characters causes the biggest issue in the character recognition procedure due to the freestyle writings of the individual and varies from person to person. There are many different shapes and orientations that a letter can take. Firstly, CNN models are designed from scratch, then a learning-based weighted average ensemble of deep neural network models (WEnDNN) is proposed to classify 10 digits and 47 characters present in alphabet set of Odia language and to enhance the accuracy. The performance of proposed WEnDNN model with EnDNN and machine learning models, namely, like RF, SVM, k NN and XG Boost trained on hand-crafted extracted features by using Gabor filter and pixel intensity values, non-handcrafted extracted features from pre-trained VGG16 neural network are compared. The proposed WEnDNN OHCNR model's overall accuracy recorded as 98.78% on ISI image numeral database. In comparison to state-of-the-art techniques, it has been found that the suggested method offers superior recognition accuracy. These ensemble models can be extended to continuously learn and adapt to changing data patterns over time. This could involve online learning approaches where the ensemble is updated incrementally as new data becomes available, allowing it to stay relevant and effective in dynamic environments.

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Monitoring Student Attendance Through Vision Transformer-based Iris Recognition

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***Abstract*—In the context of the ongoing digital transformation, the effective monitoring of student attendance holds paramount significance for educational establishments. This study presents an innovative approach using Vision Transformer technology for iris recognition to automate student attendance tracking. We fine-tuned Vision Transformer models, specifically ViT-B16, ViT-B32, ViT-L16, and ViT-L32, using the CASIA-Iris-Syn dataset and focused on overcoming challenges related to intra-class variation through data augmentation techniques, including rotation, shearing, and brightness adjustments. The results reveal that ViT-L16 is the most proficient, achieving an impressive accuracy of 95.69%. Comparative analysis with prior methodologies, specifically those employing Vision Transformer with Convolutional Neural Network, underscores the superiority of our proposed ViT-L16 model. This superiority is evident across various metrics, including accuracy, precision, recall, and F1 score. The experimental setup involves the use of Jupyter Notebook, Python technologies, TensorFlow, and Keras, emphasizing evaluations based on loss, accuracy, and Confusion Matrix. ViT-L16 consistently outshines other models, showcasing its resilience in iris recognition for student attendance. This research marks a significant step towards modernizing attendance systems, offering an accurate and automated solution suitable for the evolving needs of educational settings. Future work could explore integrating additional biometric modalities and refining Vision Transformer architecture for enhanced performance and broader application in educational environments.**

Keywords*—Iris Recognition; Vision transformer; student attendance; vision transformer models; educational technology

I. Introduction

A Student Attendance System is a digital solution designed to track and manage the attendance of students in educational institutions. It offers an efficient and accurate way to record and monitor student attendance, replacing traditional manual methods. Additionally, applying Student Attendance System significantly enhance the organization, precision, and transparency within educational institutions. It can also serve as a tool for analyzing attendance patterns, identifying areas for improvement, and fostering communication between educators and parents.

Accurate and timely attendance records are fundamental for identifying student absenteeism, serving as a crucial component in promoting student retention and academic achievement [1]. By meticulously tracking attendance, educators can readily implement necessary interventions for at-risk students, facilitating their academic success.

Many educational institutions still employ manual student attendance tracking, such as roll call or sign-in sheets. These methods are inefficient, as they are time-consuming and susceptible to human error. Additionally, they lack real-time capabilities, hindering the timely identification and resolution of attendance issues. Furthermore, manual methods offer limited security and privacy compared to biometric solutions. Vision Transformer (ViT) technology seeks to address these shortcomings by automating attendance, potentially reducing educator workload [2]. ViTs leverage iris recognition, a biometric approach offering greater accuracy, security, and real-time monitoring than manual methods. This transformation can streamline administrative processes and align with the ongoing integration of technology within the educational sector.

Traditional attendance tracking solutions often rely on manual methods (roll calls, sign-in sheets), card-based systems (RFID [3][4]), or biometric technologies [5][6]. While these methods offer varying degrees of utility, they frequently encounter limitations in efficiency, security, and accuracy. The ViT-based approach demonstrates a technological evolution in attendance management, leveraging sophisticated image processing and machine learning for iris recognition. This translates to superior security and precision, minimizing the potential for fraudulent activity. Furthermore, process automation makes the ViT approach a uniquely efficient and dependable solution within educational and organizational settings.Haut du formulaire.

Iris recognition technology is being integrated into student attendance systems to automate and enhance monitoring and documentation processes. This biometric approach involves capturing and analyzing the unique patterns within the iris (the colored ring surrounding the pupil) [7]. Extracted features, including crypts, furrows, and freckles, serve as the basis for generating unique biometric templates for each individual.

Integrating AI, especially Vision Transformer technology, demonstrates a commitment to technological advancement within the educational institution. It positions the institution at the forefront of leveraging innovative solutions for routine tasks.

Addressing this challenge, we propose an innovative method for handling student attendance in educational institutions through the application of Computer Vision. Our strategy involves the detection and recognition of students' irises in classrooms utilizing a VIT. The primary focus of this paper is the creation of a transformer model designed specifically for the identification and recognition of iris images.

The specific tasks were carried out according to the following steps:

- Fine-tuning various Vision Transformer models to evaluate their performance in iris image classification.
- Utilizing a dataset from CASIA-Iris-Syn to assess the effectiveness of the proposed method.
- Evaluating the performance and accuracy of different Vision Transformer models, including ViT-B16, ViT-B32, ViT-L16, and ViT-L32, for the identification and classification of iris images.
- The results achieved demonstrated high performance, with an accuracy rate of 95.69% for iris image classification.

The subsequent sections of this paper are organized as follows: Section 2 offers a review of the existing studies correlated to iris image recognition in attendance systems and investigates ViT applications in image processing. Section 3 outlines the materials and methods utilized in the experimental approach. Moving forward to Section 4, the paper examines the results obtained and conducts a performance evaluation. Section 5 provides a comparative analysis of the proposed models. Lastly, Section 6 encapsulates the conclusions derived from this study.

II. Related Work

Various studies have explored different methods for monitoring attendance, Okokpujie et al. [8] implemented a Student Attendance System that utilizes Iris Biometric Recognition. The experimental findings indicate that the system operates through a web-based platform. Student identification is achieved by comparing the acquired iris image with the database entries. The system assigns an integer value of (1) for a successful match and (0) for no match, with these outcomes are then stored in a MySQL-created database.

Shaban et al. [9] proposed a multimodal system utilizing ear and iris biometrics at the feature fusion stage to recognize students in electronic examinations (E-exams) amid the COVID-19 pandemic. The approach attained a precision rate of 92.6%.

Hassan et al. [10] devised a technique for iris segmentation comprising two stages. Initially, it identifies the outer iris boundary, followed by the detection of the inner iris boundary in the second stage. The method underwent testing on CASIA iris image datasets V1 and V4, yielding accuracy results of 100% and 99.16% respectively.

Trabelsi & Shuaib, [11] proposed a biometric attendance system using fingerprint and iris recognition to improve accuracy and security in educational settings. This system addresses limitations of manual methods by offering reliable and efficient student identification, enhancing overall attendance recording processes. Similarly, Adamu, [12] introduced an advanced system integrating fingerprint and iris biometrics for attendance management in higher education. This system replaces traditional methods with a secure, efficient, and accurate approach. Utilizing fingerprint and iris scanners at lecture entrances, it verifies student identities against stored biometric data, enabling real-time tracking and reporting.

Kadry & Smaili, [13] implemented a wireless attendance management system incorporating Daugman's algorithm (Daugman, 2003) for iris recognition. This biometrics-based system, integrated with wireless technology, addresses issues related to inaccurate attendance records and surpasses the challenges associated with establishing a dedicated network for this purpose.

Khatun et al. [14] introduced the Iris Recognition Attendance Management System, which employs a camera to capture real-time images of the human iris, and storing this data in a database. The system utilizes the Gray-coding algorithm in MATLAB data analysis software to compute the iris radius. Employing MATLAB, it compares the radius of each individual with the previously stored value and automatically sends the attendance report to a predefined email address, eliminating the need for human intervention.

Sujatha et al. [15] proposed a solution for a biometric-based attendance system utilizing iris recognition, interfaced with NI MYRIO. The proposal emphasizes the robustness of iris recognition, highlighting its reliability, accuracy, and efficiency attributed to the unique and immutable characteristics of the iris. Furthermore, NI LABVIEW, a graphical user interface-based software, facilitates real-time monitoring and attendance management. The integration of features such as SMS notifications for absentees and the generation of Excel sheets enhances the overall functionality of the system.

Joshy & Jalaja. [16] introduced a biometric authentication system based on the Internet of Things (IoT), and emphasizes the use of iris recognition for its unparalleled accuracy and security. The proposed system incorporates a hybrid encryption algorithm (Blowfish and RSA) for securing data transmitted over the Internet and implements a two-step authentication process. Developed as an embedded system for secure employee authentication.

Lad & More, [17] developed a student attendance system leveraging iris detection technology, which is acknowledged as the most reliable and accurate form of biometric identification. This initiative aims to address the shortcomings of commercial systems by offering an open-source alternative. The system employs the Hough transform for automatic iris segmentation, normalizes the iris region, and uses 1D Log-Gabor filters for feature extraction. These steps are designed to enhance the efficiency and accuracy of attendance tracking in educational contexts.

In [18], the authors presented a multimodal biometric system utilizing Convolutional Neural Networks (CNN) and transfer learning for iris recognition. It aims to overcome limitations in unimodal biometric methods by focusing on deep learning models for analyzing both left and right irises. Employing back-propagation with Adam's optimization, the system demonstrates high accuracy on public datasets, IITD and CASIA-Iris-V3 Interval, achieving up to 99% accuracy. This study underscores the effectiveness of combining CNN characteristics and transfer learning in real-time iris recognition, enhancing security and identification processes in various conditions.

In recent studies, the Vision Transformer has been employed for image classification and identification, representing a neural network architecture tailored specifically for image processing in computer vision applications [19].The ViT is a neural network crafted for image processing in computer vision. It employs a self-attention mechanism commonly found in natural language processing, setting it apart from traditional image processing architectures like CNNs and RNNs. Introduced to address limitations in handling image data, ViT offers robust image feature representation and requires fewer computational resources for training compared to CNNs [20].

Elpina & Kusuma,[21] introduced a Swin Transformer model for feature extraction in food image classification, incorporating an SVM classifier. The methodology underwent training and evaluation utilizing the Food-101 Dataset, resulting in an impressive accuracy (ACC) of 97.61%.

Mehta et al.[22] introduced a method for ear recognition that exercises the ViT network architecture, attaining a recognition accuracy surpassing 99.36%.

Latif et al.[23] introduced a hybrid model combining ViT and Convolutional Neural Network (CNN) for the identification and verification of iris images. The hybrid model demonstrated an accuracy of up to 93.66% in recognizing iris patterns.

Ha et al.[24] employed the Vision Transformer architecture to extract data features and categorize X-ray images as either pneumonia-positive or negative. Experimental findings reveal that the Vision Transformer algorithm consistently yields favorable classification outcomes, achieving an accuracy of approximately 94%.

III. Materials and Methods

A. Proposed Methodologies

This paper investigates the enhancement of student attendance management through a novel ViT-based iris recognition approach. This approach leverages automation to improve the accuracy and efficiency of attendance tracking.

Fig. 1 illustrates our proposed Vision Transformers approach for iris identification and recognition.

B. Dataset

Our study utilized a dataset sourced from CASIA-Iris-Syn, featuring 8533 artificially generated iris images distributed across 50 classes, as illustrated in Fig. 2. The textures of these iris images were automatically synthesized from a subset of CASIA-IrisV1.Subsequently, the iris ring regions were incorporated into authentic iris images, augmenting the realism of the artificial iris images. Intra-class variations, including deformation, blurring, and rotation, were introduced into the synthesized iris dataset. The training dataset comprises 5814 iris images in JPG format. The validation and test sets were assessed using new databases, consisting of 1027 images and 1692 images, respectively. A graphical illustration of the configuration of this dataset as depicted in Fig. 3.

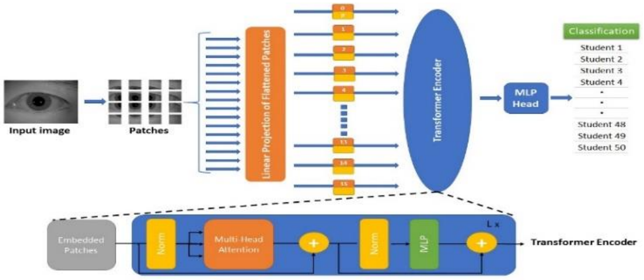


Fig. 1. Visualization of our proposed Vision Transformer (ViT) model for identifying and recognizing iris images. Initially, the input image undergoes segmentation into fixed-size patches, which are subsequently flattened. Following this, position embeddings are introduced, and the resulting sequence of vectors is then passed through a standard Transformer encoder. The inspiration for this illustration is derived from [2].

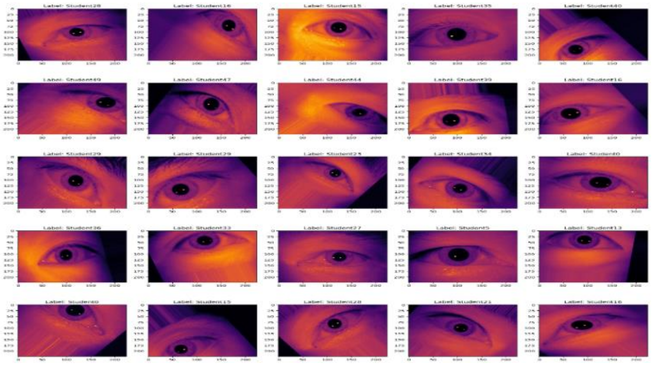


Fig. 2. Example of iris images in the Iris Dataset (50 classes).

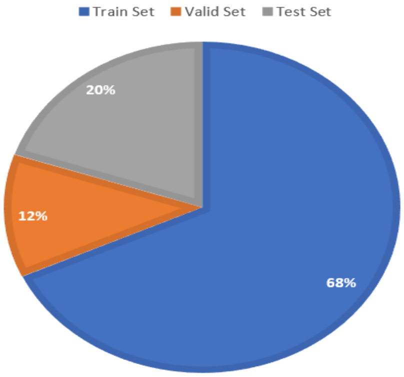


Fig. 3. Distribution of the Iris dataset (50 classes).

C. Data Augmentation Technique

Data augmentation serves as a pivotal technique in machine learning, aimed at artificially expanding the scale of a training dataset through the application of diverse transformations to the existing data. This strategy proves instrumental in enhancing the generalization and resilience of machine learning models. Its significance becomes more pronounced when dealing with a restricted training dataset size. By creating novel variations to pre-existing data, data augmentation serves a dual purpose of mitigating overfitting risks and enabling the model to capture more resilient features. Widely utilized across domains like image classification, object detection, and segmentation, data augmentation emerges as a fundamental tool for bolstering the performance and adaptability of machine learning models.

In this research, our emphasis was directed towards various data augmentation methods. The precise parameters selected for each operation are detailed in Table I.

The Table I outlines the specific parameters employed for various data augmentation operations. Rotation is set at 30 degrees, shearing at 0.2 radians, and zooming within a range of 0.2. Horizontal and vertical flips are enabled, and brightness is varied within the range of 0.4 to 1.5. These meticulously chosen parameters contribute to the augmentation of the training dataset, and ultimately bolstering the model's robustness and performance.

TABLE I. DATA AUGMENTATION PARAMETERS

Operations	Values
Rotation	30 degrees
Shearing	0.2 radians
Zooming (range)	0.2
Horizontal flip	True
Vertical flip	True
Brightness	[0.4, 1.5]

D. Vision Transformer (ViT)

The Vision Transformer presents a revolutionary deep learning architecture designed to tackle computer vision tasks, challenging the conventional prominence of convolutional neural networks. Originating from the paper titled "An Image is Worth 16x16 Words: Transformers for Image Recognition" by Alexey Dosovitskiy et al.[2], ViT extends the transformer architecture, initially crafted for natural language processing, into the realm of images. This adaptation involves the incorporation of self-attention mechanisms, enabling the model to adeptly capture long-range dependencies within the input data. ViT's introduction marks a paradigm shift, opening up new possibilities for image recognition and paving the way for diverse applications beyond the confines of traditional CNN-based approaches.

In contrast to processing the entire image in a holistic manner, the Vision Transformer adopts a strategy of partitioning the input image into fixed-size, non-overlapping patches. Subsequently, each of these patches undergoes a linear embedding, transforming it into a flat vector and composing the input sequence for the transformer. To preserve spatial information, positional embeddings are introduced to the patch embeddings. This addition enables the model to discern the spatial relationships existing between distinct patches, ensuring a nuanced understanding of the overall image structure. The incorporation of such mechanisms enhances ViT's capacity to effectively process and interpret intricate spatial features within images.

ViT models are typically pre-trained on large datasets, such as ImageNet, using a contrastive learning framework. This pre-training helps the model learn rich visual representations. The pre-trained ViT model is fine-tuned for specific tasks by adding a linear classification head on top. The model can be fine-tuned for various computer vision tasks such as image classification, object detection, and segmentation.

ViT has shown good scalability, performing well on both small and large datasets. This scalability is advantageous for adapting the model to different tasks.

In this research, the Vision Transformer architecture is crafted with adjustable dimensions to suit specific requirements. Additionally, each parameter in the vision transformer holds a crucial role, and their descriptions are outlined as follows:

- image_size=224: This parameter defines the preferred dimensions (width and height) of the input images for the model. In this instance, the images are expected to have dimensions of 224x224 pixels.
- patch_size=16: The images undergo segmentation into smaller patches, and this parameter determines the size (width and height) of each patch. In this case, each patch measures 16x16 pixels.
- num_classes=50: This parameter signifies the number of classes involved in the classification task. In this particular example, the model is configured to categorize inputs into 50 classes.
- dropout=0.2: This parameter governs the dropout rate, a regularization technique employed to mitigate overfitting. It involves randomly setting a fraction of input units to 0 during training.

E. Evaluation Metrics

The assessment of prediction algorithms in this study relies on various performance metrics. The paper examines the subsequent evaluation metrics to gauge the efficacy of the proposed model:

1) Accuracy score: The accuracy score is a performance metric used to measure the overall correctness of a predictive model. It is calculated by dividing the number of correct predictions by the total number of predictions and is often expressed as a percentage[25]. The formula for accuracy is shown in equation (1).

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (1)$$

2) Precision: Precision is a performance metric used in classification tasks to assess the accuracy of the positive predictions made by a model. It is defined as the ratio of true positive predictions to the total number of positive predictions (both true positives and false positives) [25].The formula for precision is shown in equation (2).

$$\text{Precision} = (\text{TP})/(\text{TP} + \text{FP}) \quad (2)$$

3) Recall: Recall, also known as sensitivity or true positive rate, is a performance metric used in classification tasks to evaluate a model's ability to correctly identify all relevant instances of a particular class. It is the ratio of true positive predictions to the total number of actual positive instances (including both true positives and false negatives) [25].The formula for recall is shown in equation (3):

$$\mathrm{Recall} = (\mathrm{TP})/(\mathrm{TP} + \mathrm{FN}) \qquad (3)$$

4) F1-score: The F1 score is a metric commonly used in classification tasks that combines both precision and recall into a single measure. It is particularly useful when there is an uneven class distribution (imbalanced datasets) and provides a balance between the precision and recall metrics [25].The formula for the F1 score is shown in equation (4):

$$\mathrm{F1} = 2 * (\mathrm{precision} + \mathrm{recall})/(\mathrm{precision} + \mathrm{recall}) \qquad (4)$$

5) Matthews correlation coefficient: The Matthews correlation coefficient (MCC) is a metric used to evaluate the performance of binary classification models, particularly when dealing with imbalanced datasets. It takes into account true positives, true negatives, false positives, and false negatives. The formula for Matthews correlation coefficient is shown in equation (5):

$$\mathrm{MCC} = \frac{\mathrm{TP}\times\mathrm{TN}-\mathrm{FP}\times\mathrm{FN}}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \times 100 \qquad (5)$$

IV. Results and Discussions

The primary objective of this research is to develop a transformer model designed for the identification and recognition of iris images. The model underwent training using both regular and augmented images, with where data augmentation employed to enhance the training dataset. Training involved 5814 images, validation with 1027 images, and testing utilized 1692 images. The network layers were subsequently frozen and fine-tuned with dense layers containing 1024, 512, 256, and 50 neurons, respectively.

Table II summarizes the performance metrics of different ViT models, each trained for 50 epochs, in the context of iris image identification and recognition. Notably, the ViT-L16 model emerges as the top performer with an accuracy score of 95.69%, demonstrating its effectiveness in accurately classifying iris images. ViT-L32, ViT-B32, and ViT-B16 also exhibit commendable performance, achieving accuracy scores of 94.03%, 93.26%, and 92.02% respectively. In terms of precision, recall, F1 score, and Matthews Correlation Coefficient (MCC), ViT-L16 consistently outperforms the other models, emphasizing its robustness in various evaluation criteria. These results indicate that the ViT-L16 model, with its customizable dimensions and advanced architecture, proves to be particularly effective in iris recognition tasks, demonstrating its potential for applications such as student attendance using Vision Transformer technology.

A. Experimental Setup

The experimental setup utilized Jupyter Notebook along with Python technologies such as NumPy, Pandas, and OpenCV for image processing tasks. For implementing classifiers, Scikit-Learn, Anaconda, and Python 3.9 were employed. The Vision Transformer model underwent training and testing processes using TensorFlow and Keras, leveraging Google Colab PRO T4-GPU with reported memory at 51GB and storage space at 166.77GB for refined computational capabilities.

TABLE II. Accuracy Score, Precision Score, Recall Score, F1 Score and MCC of our Vision Transformers Models

Model	Number of epochs	Accuracy Score (%)	Precision Score (%)	Recall Score (%)	F1Score (%)	MCC (%)
ViT-B16	50	92.02	93.83	92.02	91.85	91.91
ViT-B32	50	93.26	93.87	93.26	9327	93.14
ViT-L16	50	95.69	96.08	95.69	95.64	95.61
ViT-L32	50	94.03	94.65	94.03	93.88	93.93

B. Loss and Accuracy

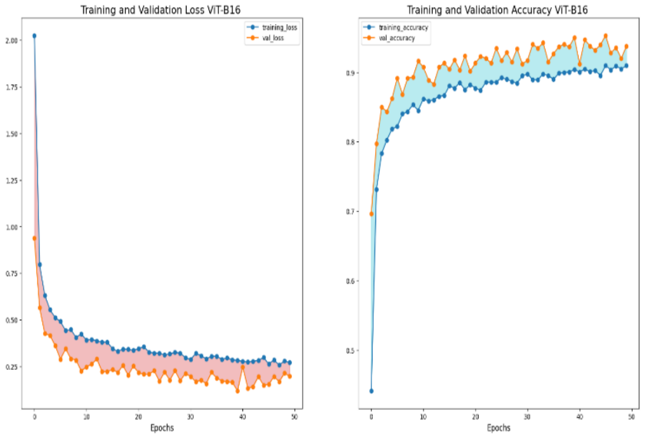
1) Loss: serves as an indicator of the model's performance on training data, gauging the discrepancy between predicted values and actual ground truth. The training objective involves minimizing the loss, with a lower value indicating closer alignment between model predictions and actual values.

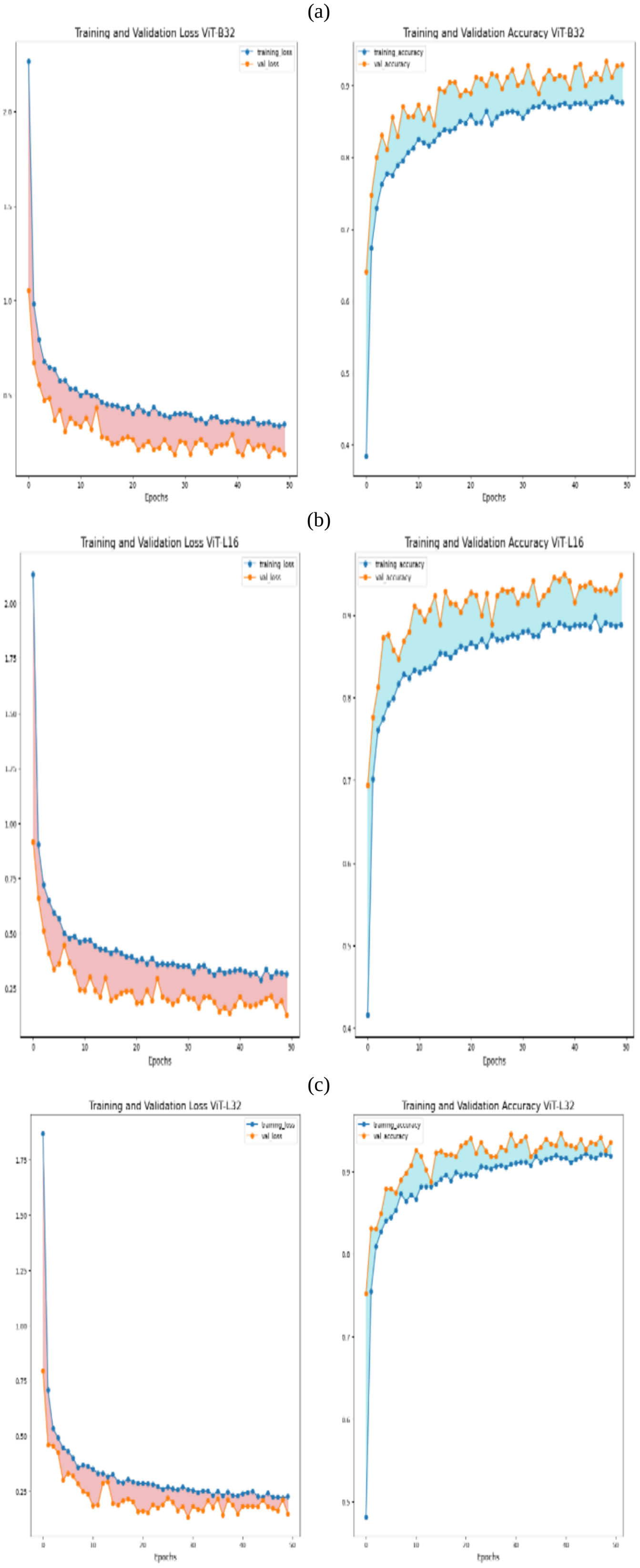
2) Accuracy: serves as a metric for the overall correctness of the model, determining the ratio of correctly predicted instances to the total instances. The goal in both training and testing phases is to maximize accuracy, as a higher value signifies a greater proportion of correct predictions.

In Fig. 4, the evaluation of loss and accuracy is depicted for the ViT-B16, ViT-B32, ViT-L16, and ViT-L32 models. The results clearly indicate that the ViT-L16 model exhibits superior performance, confirming its heightened effectiveness when compared to the other models.

C. Confusion Matrix

An additional evaluation metric, the Confusion Matrix, was utilized to assess the overall effectiveness of a classification model. The Confusion Matrix serves as a tabular summary, offering a detailed breakdown of the model's predictions in comparison to the actual class labels. The evaluation outcomes for the mentioned algorithms, using these criteria, are illustrated in Fig. 5.



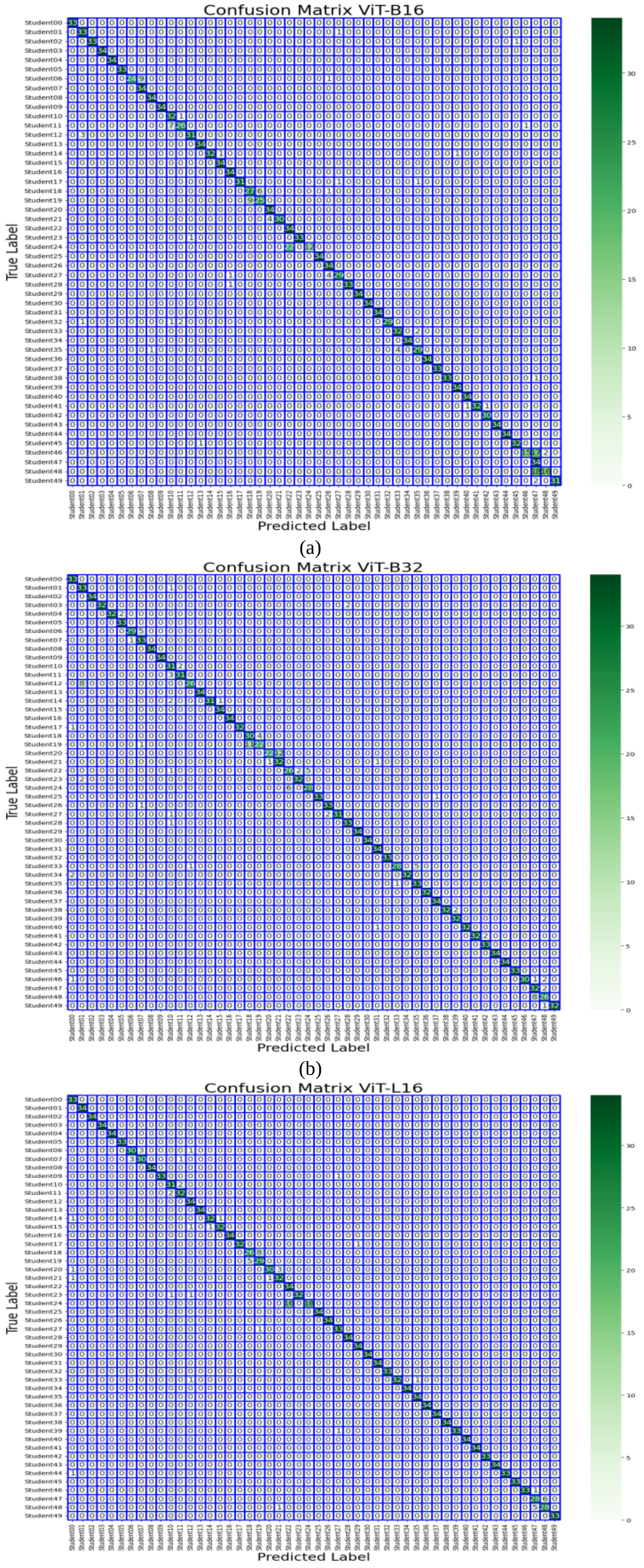

(a)

(b)

(c)

(d)

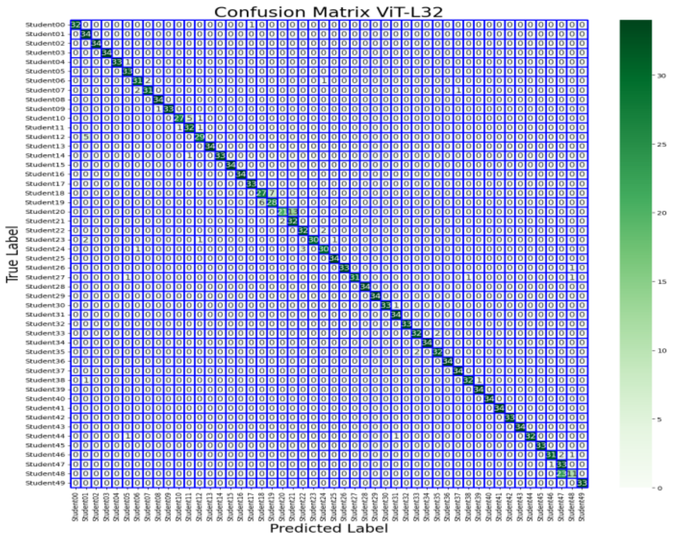
Fig. 4. Loss and Accuracy of ViT-B16 (a), ViT-B32 (b), ViT-L16 (c), and ViT-L32 (d).



(a)

(b)

(c)



(d)

Fig. 5. Confusion Matrix of ViT-B16 (a), ViT-B32 (b), ViT-L16 (c), and ViT-L32 (d).

Fig. 5(a) presented the recognition outcomes achieved using the ViT-B16 model. The average count of accurate recognitions for each category was 31.16. The expected correct recognition count ranged between 33 and 34. As a result, the average accuracy attained by the ViT-B16 model was 92.02%.

In Fig. 5(b), the ViT-B32 model's recognition results were presented. The mean correct recognition count for each category was 31.56, with the expected correct recognition count ranging 33 and 34. As a result, the average accuracy of the ViT-B32 model was 93.26%.

Moving to Fig. 5(c), it demonstrated the recognition outcomes of the ViT-L16 model. The mean correct recognition number for each category was 32.44, with the expected correct recognition number ranging between 33 and 34. The ViT-L16 model achieved an average accuracy of 95.69%.

In Fig. 5(d), the recognition results of the ViT-L32 model were depicted. The mean correct recognition number for each category was 31.82, and the expected correct recognition number ranged between 30 and 34. The average accuracy of the ViT-L32 model was 94.03%.

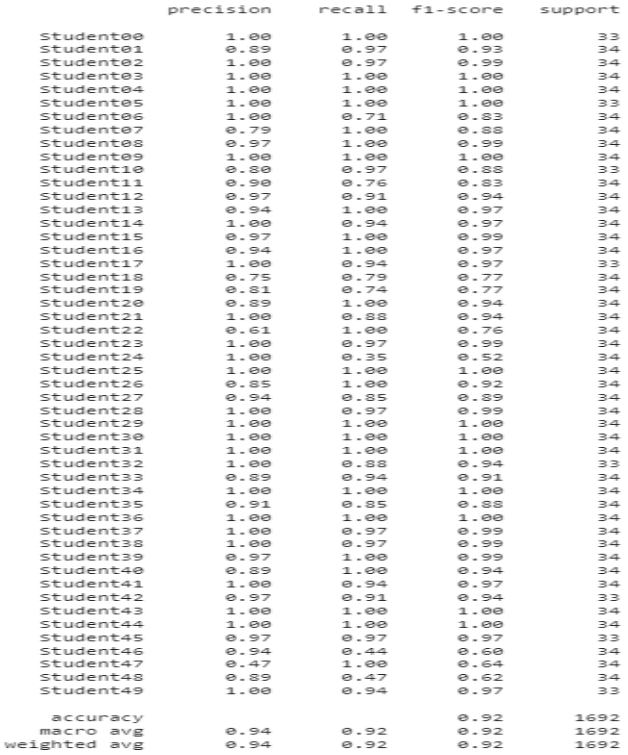
D. Classification Report

Fig. 6(a) displays the classification report for the ViT-B16 model, indicating precision values for iris classes ranging from 0.47 to 1. Additionally, the recall performance values for iris classes fall within the range of 0.35 to 1, with corresponding support values between 33 and 34. F1 scores for the iris classes vary from 0.52 to 1. The ViT-B16 model achieves an accuracy of 0.92 (92%) based on the F1 score, considering 1692 support values. The macro and weighted averages for precision and recall are 0.94, 0.92, 0.94, and 0.92, and the f1 scores are 0.92 and 0.92, each with support values of 1692.

Fig. 6(b) exhibits the classification report of the ViT-B32 model, revealing precision values within the range of 0.73 to 1 for iris classes. The recall performance spans from 0.65 to 1 across iris classes, accompanied by corresponding support values ranging from 33 to 34. F1 scores for the iris classes vary from 0.73 to 1. The ViT-B32 model attains an accuracy of 0.93 (93%) based on the F1 score, taking into account 1692 support values. The macro and weighted averages for precision and recall stand at 0.94, 0.93, 0.94, and 0.93, with f1 scores of 0.93 and 0.93, respectively, supported by 1692 instances.

Fig. 6(c) illustrates the ViT-L16 model's classification report, delineating precision values for iris classes ranging from 0.84 to 1. Likewise, the recall performance for iris classes spans from 0.53 to 1, accompanied by support values ranging between 33 and 34. F1 scores for the iris classes vary between 0.69 and 1. The accuracy of the ViT-B16 model stands at 0.96 (96%) based on the F1 score, considering 1692 support values. The macro and weighted averages for precision and recall are 0.96, 0.96, 0.96, and 0.96, respectively, with f1 scores of 0.96 and 0.96, supported by 1692 instances.

In Fig. 6(d), the classification report of the ViT-L32 model illustrates precision values for iris classes spanning from 0.57 to 1. Moreover, recall performance values for iris classes range from 0.32 to 1, with corresponding support values falling between 33 and 34. F1 scores for the iris classes are distributed within the range of 0.46 to 1. The ViT-B16 model attains an accuracy of 0.94 (94%) based on the F1 score, taking into account 1692 support values. The precision and recall values for both macro and weighted averages are 0.95, 0.94, 0.95, and 0.94, with F1 scores of 0.94 and 0.94, respectively, supported by 1692 instances.

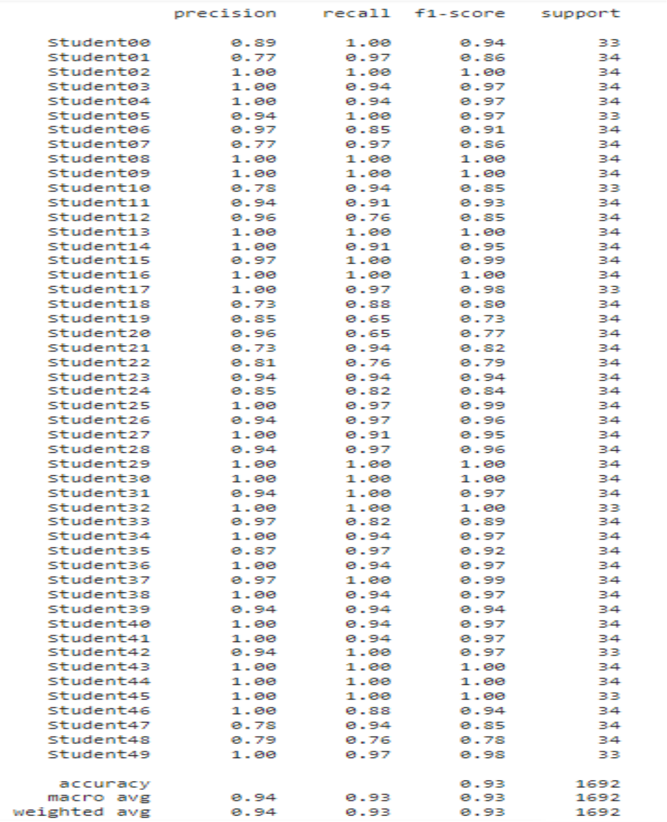


```
              precision    recall  f1-score   support

   Student00       1.00      1.00      1.00        33
   Student01       0.89      0.97      0.93        34
   Student02       1.00      0.97      0.99        34
   Student03       1.00      1.00      1.00        34
   Student04       1.00      1.00      1.00        34
   Student05       1.00      1.00      1.00        33
   Student06       1.00      0.71      0.83        34
   Student07       0.79      1.00      0.88        34
   Student08       0.97      1.00      0.99        34
   Student09       1.00      1.00      1.00        34
   Student10       0.80      0.97      0.88        33
   Student11       0.90      0.76      0.83        34
   Student12       0.97      0.91      0.94        34
   Student13       0.94      1.00      0.97        34
   Student14       1.00      0.94      0.97        34
   Student15       0.97      1.00      0.99        34
   Student16       0.94      1.00      0.97        34
   Student17       1.00      0.94      0.97        33
   Student18       0.75      0.79      0.77        34
   Student19       0.81      0.74      0.77        34
   Student20       0.89      1.00      0.94        34
   Student21       1.00      0.88      0.94        34
   Student22       0.61      1.00      0.76        34
   Student23       1.00      0.97      0.99        34
   Student24       1.00      0.35      0.52        34
   Student25       1.00      1.00      1.00        34
   Student26       0.85      1.00      0.92        34
   Student27       0.94      0.85      0.89        34
   Student28       1.00      0.97      0.99        34
   Student29       1.00      1.00      1.00        34
   Student30       1.00      1.00      1.00        34
   Student31       1.00      1.00      1.00        34
   Student32       1.00      0.88      0.94        33
   Student33       0.89      0.94      0.91        34
   Student34       1.00      1.00      1.00        34
   Student35       0.91      0.85      0.88        34
   Student36       1.00      1.00      1.00        34
   Student37       1.00      0.97      0.99        34
   Student38       1.00      0.97      0.99        34
   Student39       0.97      1.00      0.99        34
   Student40       0.89      1.00      0.94        34
   Student41       1.00      0.94      0.97        34
   Student42       0.97      0.91      0.94        33
   Student43       1.00      1.00      1.00        34
   Student44       1.00      1.00      1.00        34
   Student45       0.97      0.97      0.97        33
   Student46       0.94      0.44      0.60        34
   Student47       0.47      1.00      0.64        34
   Student48       0.89      0.47      0.62        34
   Student49       1.00      0.94      0.97        33

    accuracy                           0.92      1692
   macro avg       0.94      0.92      0.92      1692
weighted avg       0.94      0.92      0.92      1692
```

(a)

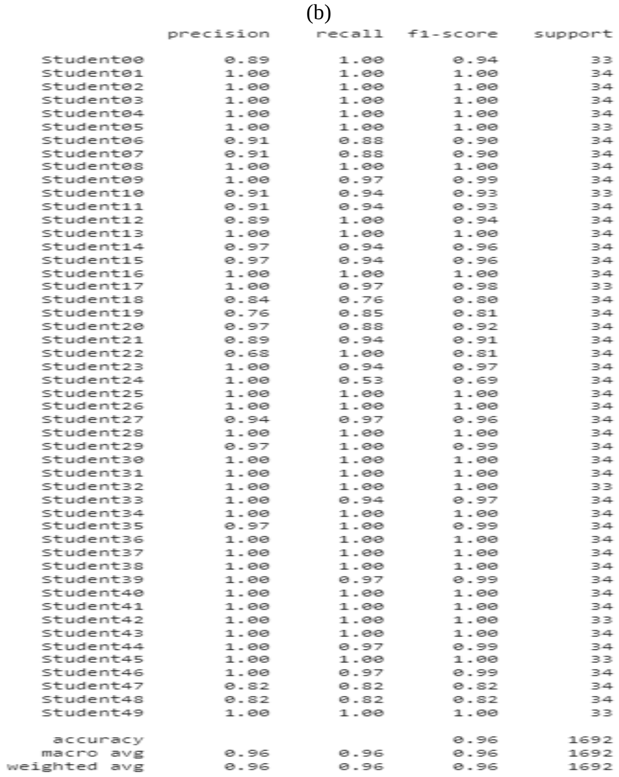


```
              precision    recall  f1-score   support

   Student00       0.89      1.00      0.94        33
   Student01       0.77      0.97      0.86        34
   Student02       1.00      1.00      1.00        34
   Student03       1.00      0.94      0.97        34
   Student04       1.00      0.94      0.97        34
   Student05       0.94      1.00      0.97        33
   Student06       0.97      0.85      0.91        34
   Student07       0.77      0.97      0.86        34
   Student08       1.00      1.00      1.00        34
   Student09       1.00      1.00      1.00        34
   Student10       0.78      0.94      0.85        33
   Student11       0.94      0.91      0.93        34
   Student12       0.96      0.76      0.85        34
   Student13       1.00      1.00      1.00        34
   Student14       1.00      0.91      0.95        34
   Student15       0.97      1.00      0.99        34
   Student16       1.00      1.00      1.00        34
   Student17       1.00      0.97      0.98        33
   Student18       0.73      0.88      0.80        34
   Student19       0.85      0.65      0.73        34
   Student20       0.96      0.65      0.77        34
   Student21       0.73      0.94      0.82        34
   Student22       0.81      0.76      0.79        34
   Student23       0.94      0.94      0.94        34
   Student24       0.85      0.82      0.84        34
   Student25       1.00      0.97      0.99        34
   Student26       0.94      0.97      0.96        34
   Student27       1.00      0.91      0.95        34
   Student28       0.94      0.97      0.96        34
   Student29       1.00      1.00      1.00        34
   Student30       1.00      1.00      1.00        34
   Student31       0.94      1.00      0.97        34
   Student32       1.00      1.00      1.00        33
   Student33       0.97      0.82      0.89        34
   Student34       1.00      0.94      0.97        34
   Student35       0.87      0.97      0.92        34
   Student36       1.00      0.94      0.97        34
   Student37       0.97      1.00      0.99        34
   Student38       1.00      0.94      0.97        34
   Student39       0.94      0.94      0.94        34
   Student40       1.00      0.94      0.97        34
   Student41       1.00      0.94      0.97        34
   Student42       0.94      1.00      0.97        33
   Student43       1.00      1.00      1.00        34
   Student44       1.00      1.00      1.00        34
   Student45       1.00      1.00      1.00        33
   Student46       1.00      0.88      0.94        34
   Student47       0.78      0.94      0.85        34
   Student48       0.79      0.76      0.78        34
   Student49       1.00      0.97      0.98        33

    accuracy                           0.93      1692
   macro avg       0.94      0.93      0.93      1692
weighted avg       0.94      0.93      0.93      1692
```

(b)

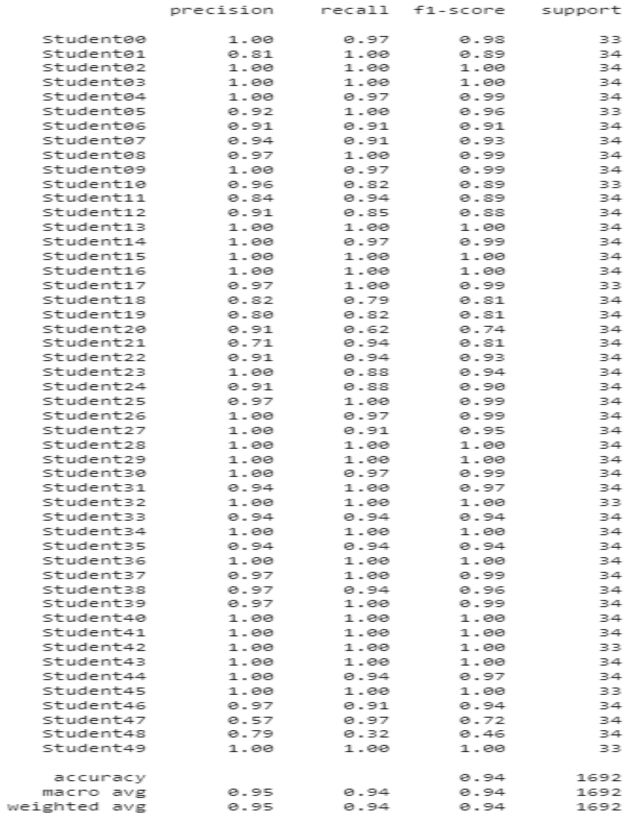


```
              precision    recall  f1-score   support

   Student00       0.89      1.00      0.94        33
   Student01       1.00      1.00      1.00        34
   Student02       1.00      1.00      1.00        34
   Student03       1.00      1.00      1.00        34
   Student04       1.00      1.00      1.00        34
   Student05       1.00      1.00      1.00        33
   Student06       0.91      0.88      0.90        34
   Student07       0.91      0.88      0.90        34
   Student08       1.00      1.00      1.00        34
   Student09       1.00      0.97      0.99        34
   Student10       0.91      0.94      0.93        33
   Student11       0.91      0.94      0.93        34
   Student12       0.89      1.00      0.94        34
   Student13       1.00      1.00      1.00        34
   Student14       0.97      0.94      0.96        34
   Student15       0.97      0.94      0.96        34
   Student16       1.00      1.00      1.00        34
   Student17       1.00      0.97      0.98        33
   Student18       0.84      0.76      0.80        34
   Student19       0.76      0.85      0.81        34
   Student20       0.97      0.88      0.92        34
   Student21       0.89      0.94      0.91        34
   Student22       0.68      1.00      0.81        34
   Student23       1.00      0.94      0.97        34
   Student24       1.00      0.53      0.69        34
   Student25       1.00      1.00      1.00        34
   Student26       1.00      1.00      1.00        34
   Student27       0.94      0.97      0.96        34
   Student28       1.00      1.00      1.00        34
   Student29       0.97      1.00      0.99        34
   Student30       1.00      1.00      1.00        34
   Student31       1.00      1.00      1.00        34
   Student32       1.00      1.00      1.00        33
   Student33       1.00      0.94      0.97        34
   Student34       1.00      1.00      1.00        34
   Student35       0.97      1.00      0.99        34
   Student36       1.00      1.00      1.00        34
   Student37       1.00      1.00      1.00        34
   Student38       1.00      1.00      1.00        34
   Student39       1.00      0.97      0.99        34
   Student40       1.00      1.00      1.00        34
   Student41       1.00      1.00      1.00        34
   Student42       1.00      1.00      1.00        33
   Student43       1.00      1.00      1.00        34
   Student44       1.00      0.97      0.99        34
   Student45       1.00      1.00      1.00        33
   Student46       1.00      0.97      0.99        34
   Student47       0.82      0.82      0.82        34
   Student48       0.82      0.82      0.82        34
   Student49       1.00      1.00      1.00        33

    accuracy                           0.96      1692
   macro avg       0.96      0.96      0.96      1692
weighted avg       0.96      0.96      0.96      1692
```

(c)



```
              precision    recall  f1-score   support

   Student00       1.00      0.97      0.98        33
   Student01       0.81      1.00      0.89        34
   Student02       1.00      1.00      1.00        34
   Student03       1.00      1.00      1.00        34
   Student04       1.00      0.97      0.99        34
   Student05       0.92      1.00      0.96        33
   Student06       0.91      0.91      0.91        34
   Student07       0.94      0.91      0.93        34
   Student08       0.97      1.00      0.99        34
   Student09       1.00      0.97      0.99        34
   Student10       0.96      0.82      0.89        33
   Student11       0.84      0.94      0.89        34
   Student12       0.91      0.85      0.88        34
   Student13       1.00      1.00      1.00        34
   Student14       1.00      0.97      0.99        34
   Student15       1.00      1.00      1.00        34
   Student16       1.00      1.00      1.00        34
   Student17       0.97      1.00      0.99        33
   Student18       0.82      0.79      0.81        34
   Student19       0.80      0.82      0.81        34
   Student20       0.91      0.62      0.74        34
   Student21       0.71      0.94      0.81        34
   Student22       0.91      0.94      0.93        34
   Student23       1.00      0.88      0.94        34
   Student24       0.91      0.88      0.90        34
   Student25       0.97      1.00      0.99        34
   Student26       1.00      0.97      0.99        34
   Student27       1.00      0.91      0.95        34
   Student28       1.00      1.00      1.00        34
   Student29       1.00      1.00      1.00        34
   Student30       1.00      0.97      0.99        34
   Student31       0.94      1.00      0.97        34
   Student32       1.00      1.00      1.00        33
   Student33       0.94      0.94      0.94        34
   Student34       1.00      1.00      1.00        34
   Student35       0.94      0.94      0.94        34
   Student36       1.00      1.00      1.00        34
   Student37       0.97      1.00      0.99        34
   Student38       0.97      0.94      0.96        34
   Student39       0.97      1.00      0.99        34
   Student40       1.00      1.00      1.00        34
   Student41       1.00      1.00      1.00        34
   Student42       1.00      1.00      1.00        33
   Student43       1.00      1.00      1.00        34
   Student44       1.00      0.94      0.97        34
   Student45       1.00      1.00      1.00        33
   Student46       0.97      0.91      0.94        34
   Student47       0.57      0.97      0.72        34
   Student48       0.79      0.32      0.46        34
   Student49       1.00      1.00      1.00        33

    accuracy                           0.94      1692
   macro avg       0.95      0.94      0.94      1692
weighted avg       0.95      0.94      0.94      1692
```

(d)

Fig. 6. Classification report of ViT-B16 (a), ViT-B32 (b), ViT-L16 (c), and ViT-L32 (d).

The research team faced challenges during the fine-tuning process due to intra-class variations within the synthesized iris dataset. To address these limitations, data augmentation techniques such as deformation, blurring, and rotation were employed. These augmentations significantly enhanced the robustness of the Vision Transformer models, particularly the ViT-L16, by introducing artificial variations within the training data. This resulted in improved model performance on real-world iris patterns with diverse characteristics, leading to higher accuracy and reliability in iris recognition tasks. These findings demonstrate the effectiveness of data augmentation in mitigating the effects of intra-class variations and highlight the adaptability of Vision Transformer architectures for tasks like student attendance monitoring using iris recognition.

This research explored the implementation of various Vision Transformer models (ViT-B16, ViT-B32, ViT-L16, and ViT-L32) for iris-based student attendance tracking. The ViT-L16 model demonstrated the highest performance in terms of accuracy, precision, and recall. Additionally, the study confirmed the adaptability of Vision Transformer architectures for iris recognition, underscoring the importance of data augmentation in improving model robustness.

V. Comparative Analysis

Table III presents a comparative examination of outcomes derived from our approach, employing Vision Transformer models ViT-L16 and ViT-L32, juxtaposed with findings from a preceding investigation utilizing ViT with CNN. The assessment hinges on pivotal metrics, including accuracy, precision, recall, and F1 score, observed across a span of 50 epochs.

In the study delineated by [23], the ViT+CNN model attained an accuracy of 93.66% after 50 epochs, although explicit figures for precision, recall, and F1 score remain undisclosed. Our methodology, leveraging ViT-L16, outperformed these results, manifesting an elevated accuracy of 95.69%. Furthermore, precision, recall, and F1 score for ViT-L16 registered at 96.08%, 95.69%, and 95.64%, sequentially. This signifies an amelioration in our model's capacity to accurately discern and categorize instances.

The ViT-L16 model's exceptional performance likely stems from its architecture, which excels at processing global image features – a vital aspect of accurate iris recognition. Unlike hybrid ViT+CNN models, which may introduce redundancies or inefficiencies through convolutional layers, the ViT-L16 relies exclusively on self-attention mechanisms. This enables a more direct and focused learning process that emphasizes the most pertinent features without the limitations inherent in convolutional operations.

Comparative results across the ViT-L16, ViT-L32, and ViT+CNN models demonstrate a clear pattern: the pure transformer-based models (ViT-L16, ViT-L32) consistently outperform the hybrid ViT+CNN model in accuracy, precision, recall, and F1 score. This finding suggests that self-attention mechanisms within transformers may be intrinsically better suited for iris recognition in attendance systems compared to a hybrid approach. Furthermore, these results highlight the potential of pure transformer models for driving improvements in biometric recognition systems.

TABLE III. Comparison of Results with Previous Works

Authors	[23]	**Our method**	
Model	ViT+CNN	**ViT-L16**	ViT-L32
Epochs	50	50	50
Accuracy (%)	93.66	**95.69**	94.03
Precision (%)	--	96.08	94.65
Recall (%)	--	95.69	95.64
F1 score (%)	--	94.03	93.88

VI. Conclusions

In this research, we formulated diverse models utilizing Vision Transformers, including ViT-B16, ViT-B32, ViT-L16, and ViT-L32, to manage student attendance in educational institutions. The most effective model turned out to be ViT-L16. ViT-L16 underwent fine-tuning to perform identification and recognition of students' iris images, leveraging a dataset comprising 8533 iris images.

Furthermore, this research has formulated four models using the Vision Transformer methodology. An evaluation of all the models revealed that, although ViT-B16, ViT-B32, and ViT-L32 performed satisfactorily, the ViT-L16 transformer outshone all the models in terms of accuracy. A comparison of F1 score, precision, and recall provides supporting evidence that the ViT-L16 transformer surpasses all other models. Additionally, when compared with all the models, the ViT-L16 transformer required less training time with an equal number of epochs.

The Vision Transformer model demonstrated the effectiveness of ViT-L16 in identifying and recognizing students' iris patterns. The proposed method represents a notable contribution to advancing the development of a student attendance system capable of recording and monitoring attendance through iris images.

Our experiments manifested the inherent adaptability of Vision Transformer architectures to iris recognition tasks. ViT models displayed robust feature extraction capabilities, allowing for accurate and reliable identification of unique iris patterns. The incorporation of data augmentation techniques, including deformation, blurring, and rotation, played a crucial role in enhancing the robustness of the models. This approach effectively mitigated the effects of intra-class variations within the synthesized iris dataset.

Future research avenues could explore the integration of additional biometric modalities to enhance the overall security and accuracy of attendance systems. Additionally, the refinement of the Vision Transformer architecture, specifically tailored to the unique requirements of educational settings, holds potential for advancing the continuous improvement of biometric-based attendance solutions.

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Employing a Hybrid Convolutional Neural Network and Extreme Learning Machine for Precision Liver Disease Forecasting

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***Abstract*—This paper discusses the critical relevance of precise forecasting in liver disease, as well as the need for early identification and categorization for immediate action and personalized treatment strategies. The paper describes a unique strategy for improving liver disease classification using ultrasound image processing. The recommended technique combines the properties of the Extreme Learning Machine (ELM), Convolutional Neural Network (CNN), along Grey Wolf Optimisation (GWO) to form an integrated model known as CNN-ELM-GWO. The data is provided by Pakistan's Multan Institute of Nuclear Medicine and Radiotherapy, and it is then pre-processed utilizing bilateral and optimal wavelet filtering techniques to increase the dataset's quality. To properly extract significant visual information, feature extraction employs a deep CNN architecture using six convolutional layers, batch normalization, and max-pooling. The ELM serves as a classifier, whereas the CNN is a feature extractor. The GWO algorithm, based on grey wolf searching strategies, refines the CNN and ELM hyperparameters in two stages, progressively boosting the system's classification accuracy. When implemented in Python, CNN-ELM-GWO exceeds traditional machine learning algorithms (MLP, RF, KNN, and NB) in terms of accuracy, precision, recall, and F1-score metrics. The proposed technique achieves an impressive 99.7% accuracy, revealing its potential to significantly enhance the classification of liver disease by employing ultrasound images. The CNN-ELM-GWO technique outperforms conventional approaches in liver disease forecasting by a substantial margin of 27.5%, showing its potential to revolutionize medical imaging and prospects.**

Keywords*—Liver disease prognosis; convolutional neural network extreme learning machine; grey wolf optimization; patient care

I. Introduction

The liver, which is the most significant internal organ in the human body, is essential to many physiological functions. It is situated under the diaphragm in the upper-right region of the abdomen. The liver possesses a special capacity for regeneration and carries out a variety of essential tasks that maintain the body healthy [1]. It has a role in digestion, detoxification, metabolism, and the control of several biochemical procedures. The major functioning cells of the liver are called hepatocytes, and they are responsible for the organ's extensive blood supply [2]. Numerous vital processes that the liver performs are necessary to preserve homeostasis. It handles nutrition from the food people eat, which is one of its main metabolic functions. When glucose is required, the liver releases glucose from storage and manages its production of glycogen for energy. It produces albumin, which aids in maintaining blood pressure and volume, and blood-clotting components [3]. It also processes down lipids into energy or accumulates them as triglycerides through metabolism. In addition, the liver breaks down medications, detoxifies hazardous compounds, and changes ammonia into urea, which the kidneys may then eliminate. Additionally, it is essential to digestion because it produces bile, which facilitates the dissolution of lipids [4].

Hepatitis, Cirrhosis, and non-alcoholic fatty liver disease are among the most common illnesses classified under the category of liver diseases. Hepatitis, which often comes on by viral infections (such as Hepatitis A, B, or C), damages and inflames the liver [5]. The primary feature of cirrhosis is the damage of the liver cells, which is often caused by viral hepatitis, chronic drinking, or other conditions. As the designation implies, non-alcoholic fatty liver disease is characterized by the build-up of fat in liver cells and has the potential for progression [6]. Chronic liver illnesses can lead to the development of liver cancer, particularly hepatocellular carcinoma. Numerous symptoms, such as weariness, jaundice (a yellowing of the skin and eyes), stomach discomfort, black urine, and unexplained weight loss, might be indicative of liver disease. If these medical conditions are not addressed, they might deteriorate and have a significant impact on general health [7]. For instance, cirrhosis can result in liver failure and its complications, which include hepatic encephalopathy and bleeding from oesophageal varices [8]. Liver fibrosis and an increased probability of liver cancer are two outcomes of hepatitis. It's essential to have an early diagnosis and treatment for these illnesses in order to prevent them from becoming fatal. Establishing a healthy routine with a balanced diet, using alcohol in moderation, and receiving a hepatitis virus vaccination are preventive strategies for liver illnesses [9].

In contemporary medicine, the ability to detect liver disorders early and accurately is critical. Liver diseases are a broad category of illnesses [10]. The quality of life and consequences for patients can be significantly improved by immediate treatment and diagnosis. Furthermore, because liver illnesses have a significant negative impact on society and healthcare systems, early detection is a practical and life-saving approach [11]. The application of several cutting-edge technology and data analysis techniques is necessary for predicting liver disorders. In this field of study, machine learning and artificial intelligence approaches have become more popular [12]. A growing number of academics and medical professionals are analysing clinical and patient information utilizing machine learning methods, such as support vector machines, logistic regression, and artificial neural networks, to produce accurate predictions [13]. To determine the probability of liver diseases, these models take into consideration a variety of factors, such as previous medical information, outcomes of blood tests, imaging information, and more. There are significant clinical consequences for accurate liver disease prediction. It makes it possible to create individualized treatment programs and for early intervention [14]. For instance, individuals that are particularly susceptible to liver disease may benefit from attentive observation, lifestyle counselling, and hepatitis virus immunization recommendations. In situations of end-stage liver diseases, early identification can also help ensure a timely liver transplant. Predictive models lessen the overall load on healthcare systems by helping recognize at-risk patients and allocating healthcare resources optimally [15]. By utilizing predictive analytics, healthcare professionals may proactively address the international problem of liver disease.

Current liver disease prediction approaches are unable to fully capitalize on the promise of cutting-edge technology like deep learning and metaheuristic optimization since they frequently rely on conventional machine learning techniques. Conversely, the paper Liver Disease Prediction utilizing Convolutional Extreme Learning Machine offers a novel strategy that gets over the drawbacks of traditional techniques. The research leverages the capabilities of deep learning and non-adjustable hidden nodes by utilizing a hybrid model that includes an ELM for rapid categorization and a CNN for feature extraction. This integration takes advantage of ELM's faster learning rate while also improving prediction accuracy. In addition, by fine-tuning the hyperparameters with GWO, the models become more appropriate for the particular position.

The key contributions of the paper are given as follows:

- The paper presents a unique pre-processing technology for liver disease prediction that combines the capabilities of Combination Wavelet as well as Bilateral Filter. This hybrid technique seeks to efficiently decrease noise and increase significant characteristics in medical pictures or data connected with liver illness, providing a stable platform for additional investigation.
- The research contains innovative feature extraction algorithms that take advantage of Convolutional Neural Networks (CNN) capabilities. By using CNNs' structured and spatial learning abilities, the study improves the extraction of complicated patterns and discriminative characteristics required for effective liver disease categorization.
- For categorization tasks, Extreme Learning Machines (ELM) are used. ELMs are noted for their high efficiency in learning and clarity, making them ideal for dealing with big datasets commonly found in clinical studies. The use of ELM provides an efficient and accurate categorization of liver disease according to extracted characteristics.
- The study uses the Grey Wolf Optimization technique to improve the classification model's accuracy. This optimization strategy, influenced by the social structure of grey wolves, attempts to improve the ELM model's convergence speed and accuracy, hence increasing the overall efficiency and efficacy of the liver disease forecasting system.
- The study assesses the suggested approach for detecting liver illness using important metrics such as precision, sensitivity, accuracy, and the F1 score. It employs 10-fold cross-validation to ensure robustness and gives a thorough grasp of the model's performance in various phases and settings, offering vital insights into its dependability and adaptability in everyday life medical contexts.

The rest of the section is organized as shown below. Section II illustrates literature works on liver disease prediction. Section III gives the Problem Statement. Section IV covers the proposed framework for the liver disease prediction. Section v illustrates the performance measures and summarizes the findings. Section VI provides the conclusion.

II. Related Works

Methods involving machine learning are being used more and more frequently in the modern day in the fields of medical research to identify numerous disorders, such as liver disease. This fatal illness claims a significant number of lives around the world [16]. Early therapy can be beneficial to the patient's recovery if the condition is diagnosed when it is in its early stages. Utilizing supervised machine learning categorization methods to detect liver disease is provided in the study article. In order to recognize the features of liver illness that are most significantly linked together, the study also used a least absolute contraction and selection operator characteristic selection approach on the dataset it had access to. The algorithms' estimations for the illness are evaluated for preciseness, sensitivity, accuracy, and f1-score values using 10-fold cross-validation. With LASSO included, it has been found that the decision tree approach performs optimally. A comparison with contemporary studies is also made to demonstrate the relevance of the suggested system. The possible difficulties of applying the results to various patient demographics or medical environments are not discussed in the research, though. It is critical to recognize the study's relevance to actual clinical practice's limits.

Individuals with chronic liver illness may experience acute-on-chronic liver failure, a clinical condition characterized by sudden hepatic decompensation and a significant short-term death rate. Organ failure, severe generalized inflammation, and a terrible outcome are its defining features [17]. Triaging and prognosticating patients with ACLF is feasible with certain liver-specific prognosis ratings and organ dysfunctions. The purpose of the research is to determine how well artificial neural networks, which functionally resemble biological neural systems, are capable of predicting the mortality associated with liver disease after ninety days. In the study, ANN was assessed in ACLF patients. A significant factor in accurately forecasting patients' short-term mortality is artificial neural networks. Its use with ACLF individuals can be beneficial since it simplifies and automated the process for recognizing individuals who are more likely to die. Artificial neural networks have a great deal of promise to help doctors make decisions, prioritize patients who need liver transplants right away, and forecast death and side effects. Even while the ANN model shows excellent precision, it might not be very interpretable. Understanding the variables that affect forecasts is essential for anyone working in the medical industry. Insufficient interpretability could undermine the model's acceptability and confidence among clinicians [18].

Even with the most recent and advanced equipment, medical professionals still have difficulties in accurately and early predicting liver disease in their patients. In the medical field, support vector machines are extensively utilized. Its effectiveness in generating quality diagnostic variables has been demonstrated. Support vector machine hyperparameter optimization may additionally enhance these outcomes. The suggested approach is predicated on using the crow search technique to optimize support vector machines. With the use of an improved support vector machine classifier, liver illness information from India may be accurately diagnosed. To demonstrate the effectiveness of the suggested method, a comparison with other comparable state-of-the-art algorithms is made. For every metric used for comparison, the efficacy of CSA-SVM is determined to be exceptional when compared to all other techniques. On the other hand, the dataset, code, and repeatability model are not made available in the work. In research related to science, repeatability and transparency are crucial [19].

Accessible medical facilities are essential for individuals in today's world, since healthcare is becoming an increasingly crucial component of daily life. The primary goal of this work is to use feature selection and categorization techniques in software engineering to forecast liver disease. The liver patient's dataset's various characteristics are utilized to forecast the degree of risk for liver disease. The Liver Patients dataset is used to test the accuracy of many methods of categorization. Numerous classifiers outputs are compared, both with and without the utilization of characteristic selection methods. Selection of characteristics and categorization estimation approaches based on software engineering concept are used in the creation of smart liver disease detection software. The article addresses using several categorization algorithms; however, it refrains from going into detail on how these algorithms' hyperparameters were adjusted or improved. Optimizing the parameters of the algorithm is crucial to attaining optimal outcomes [20].

Any condition that has the potential to damage, destroy, or impair the liver's normal function is referred to as liver disease. The death rate from liver illness has increased significantly in the world community. Numerous variables, including human behaviours, awareness problems, inadequate medical care, and delayed discovery, might be responsible for this. Early identification is essential to lower dangers and enhance treatment outcomes in order to address the ever-growing hazards posed by liver disease. As demonstrated in the present research, modern technologies like machine learning might be used to help improve its detection and diagnosis. To help in early identification, evaluation, and lowering of dangers and mortality related to the illness, a more effective approach for timely estimation of liver disease utilizing a hybrid extreme Gradient Boosting algorithm that includes hyperparameter adjustment is presented. The findings showed that the accuracy levels attained by the regression trees and chi-square automated interaction identification and categorization models were significantly higher than the traditional approach. The proposed treatment would help doctors and patients address the issue of liver damage, making sure that instances are identified earlier to avoid cirrhosis and to improve patient survival. The study demonstrated machine learning's assure in the medical field, particularly in the areas of illness monitoring and predictions [21].

The reviews of the literature investigate several machine learning techniques for the diagnosis and prognosis of liver disease. Stressing the value of early diagnosis, they address issues with interpretability and accuracy. Promising outcomes are demonstrated by strategies including CNN-ELM-GWO integration, CSA-SVM optimization, artificial neural networks for acute-on-chronic liver failure, and feature selection in intelligent software engineering applications. Even though these techniques show improved predictive power, there isn't much talk on how to apply these methods to specific demographics, how to interpret models, how to make code transparently available, and how to optimize algorithm parameters. Overall, the research highlights the promise of machine learning in enhancing the identification of liver illness, underscoring the necessity of more development and thorough investigation in clinical settings.

III. Problem Statement

Conventional machine learning algorithms for liver disease prediction have constraints concerning accessibility, transparency, and adaptation to a wide range of patient profiles and medical settings. These models frequently lack the potential to give useful information into ways to make decisions, limiting their use in clinical practice. Furthermore, more robust solutions are required to overcome the difficulties of noise as well as transparency in information from medical imaging [17]. The suggested technique, a hybrid CNN-ELM with GWO optimization, seeks to address these drawbacks. The CNN-ELM hybrid takes use of the capabilities of feature extraction and classification, while GWO optimization refines model hyperparameters. This comprehensive strategy enhances prediction accuracy while simultaneously addressing interpretability and transparency problems. Although the methods used with machine learning seem promising, there are certain obstacles that must be overcome before they can be successfully incorporated into clinical practice. The hybrid method's emphasis on optimizing learning and picture quality makes it a viable solution for obtaining accurate, early diagnosis of liver disease, eventually contributing to better outcomes for patients and lowering the worldwide effect of this life-threatening condition.

Existing methods for forecasting liver disease often rely solely on either CNNs or ELMs, but each approach has its limitations. CNNs excel at extracting hierarchical features from image data but may struggle with non-image data and require large amounts of labeled data for training. On the other hand, ELMs offer fast learning and good generalization but may not capture complex spatial relationships in image data effectively. Thus, there is a need for a hybrid approach that leverages the strengths of both CNNs and ELMs to improve the precision of liver disease forecasting. However, integrating these two disparate techniques poses challenges in terms of model architecture design, feature extraction, and optimization to ensure effective fusion of information from both modalities while mitigating overfitting and computational complexity.

IV. Liver Disease Prediction Using Convolutional Extreme Learning Machine

In the paper, an experimental analysis is conducted to thoroughly investigate the proposed method of employing a hybrid CNN and ELM for precision liver disease forecasting. To begin, a comprehensive dataset comprising a diverse range of liver disease cases, including various imaging modalities such as MRI, CT scans, and ultrasound images, as well as clinical data such as patient demographics, laboratory test results, and medical histories is curated. This dataset serves as the foundation for training, validating, and testing the hybrid model, ensuring that it is representative of real-world scenarios encountered in clinical practice.

Subsequently, the experimental setup is meticulously designed to systematically evaluate the performance of the hybrid CNN-ELM model against baseline methods and individual CNN and ELM models. The dataset is partitioned into training, validation, and testing sets, ensuring proper stratification to maintain the distributional characteristics of the data. The hyperparameters of the CNN and ELM components are then fine-tuned separately before integrating them into the hybrid framework. Throughout the experimentation process, rigorous cross-validation techniques are employed to mitigate potential biases and ensure the robustness of the findings. By systematically varying key experimental factors such as the size of the training dataset, the complexity of the model architecture, and the choice of hyperparameters, insights are gained into the effectiveness and scalability of the proposed method for precision liver disease forecasting. Ultimately, the experimental results provide empirical evidence supporting the utility and efficacy of the hybrid CNN-ELM approach, demonstrating its superiority over existing methods in accurately predicting liver disease outcomes.

This study's approach includes an extensive procedure for predicting liver disease using a dataset of 101 liver ultrasound images. In order to decrease noise and improve the clarity of the images preprocessing is employed using a hybrid technique that combined bilateral filtering and optimum wavelet transformation. Then, in order to extract crucial data from the ultrasound images, a Convolutional Neural Network with six convolutional layers, batch normalization, and max-pooling was created. Using this CNN as the feature extractor, 256 discriminant characteristics were produced for the prediction of liver disease. In order to take use of an Extreme Learning Machine's (ELM) accelerated learning speed and non-adjustable hidden node settings, these characteristics were subsequently introduced into the machine for categorization. By combining the processes of feature extraction and categorization, the hybrid CNN-ELM method improves accuracy. Lastly, to further enhance the effectiveness of the system, the CNN and ELM models' hyperparameters were adjusted using the Grey Wolf Optimization (GWO) technique. This all-encompassing method uses deep learning, metaheuristic optimization and sophisticated image processing to accurately forecast liver disease. The general framework of the proposed method is depicted in Fig. 1.

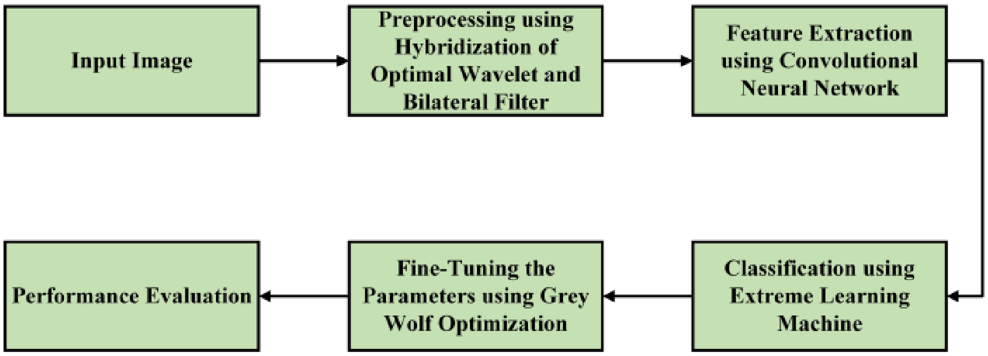
Input Image
Preprocessing using Hybridization of Optimal Wavelet and Bilateral Filter
Feature Extraction using Convolutional Neural Network
Classification using Extreme Learning Machine
Fine-Tuning the Parameters using Grey Wolf Optimization
Performance Evaluation

Fig. 1. Overall architecture of the proposed method.

A. Data Collection

There are 101 liver ultrasound images in the collection. Of them, 57 have liver abnormalities such as FLD or heterogeneous liver texture, while 44 images show healthy subjects. A Toshiba Aplio 500 B-mode digital ultrasound scanner was used to obtain all of the images at the Multan Institute of Nuclear Medicine and Radiotherapy, located in Multan, Pakistan. For tissue harmonic imaging, a convex probe was utilized at a frequency of 5 MHz [22]. Each captured image had a resolution of 560 by 450 pixels and was stored as a bitmap file. The medical expert chose 114 64×64-pixel region of interest (ROIs) for categorization into normal and abnormal for these 101 images. These chosen ROIs serve as the basis for all further processing.

B. Hybridization of Optimal Wavelet and Bilateral Filter for Preprocessing

By hybridizing the best wavelet and bilateral filter for sophisticated preprocessing, liver disease prediction can be optimized, improving diagnostic accuracy and dependability. Ultrasound preprocessing is crucial because, in contrast to other imaging modalities like CT and MRI, ultrasound images are more probable to have noise components. Essentially, a speckle noise mostly distorts the ultrasound images. Higher categorization and segmentation accuracy cannot be obtained from a noisy image. For this reason, removing noise from medical ultrasound images is an essential step. For noise reduction in the study, bilateral filters and optimum wavelet hybridization were employed. The input image is first decomposed using the bi-orthogonal 3.7 wavelet transform in the study. After then, it produces four sub-bands, including LL, LH, HL, and HH. It uses the oppositional gravitational search algorithm (OGSA) to ideally acquire the wavelet coefficient in order to enhance the overall appearance of the denoised image. Newton's law of universal gravity and mass interactions serve as the foundation for gravitational search algorithms (GSAs), which are evolutionary heuristic optimization algorithms. To improve the search performance of the GSA algorithm, combining it with an adversarial learning method. Following the decomposition, the bilateral filter is applied to eliminate any noise from the input image. One nonlinear filter that appears to be effective in denoising images is the bilateral filter, which provides spatial averaging without flattening edges. Two Gaussian filters are combined to create this filter. Fig. 2 illustrates the preprocessing procedure.

C. Feature Extraction and Classification Using Convolutional Extreme Learning Machine

1) Feature extraction employing convolutional neural network: Feature extraction is the most critical part of the categorization issue as a model's achievement is based on how effectively the key characteristics from the ultrasound images are retrieved. To enhance the model's effectiveness in categorization, it is imperative to extract the favourable aspects that have enabled discrimination between the two classes. Convolutional Neural Network feature extraction includes employing a deep architecture including convolutional layers to find and highlight relevant patterns and features in data, hence improving analysis and classification. A method for converting higher dimensional information into lower dimensional, useful, and non-redundant information is called feature extraction. It makes it possible to process information more effectively and handle it better. Because the features for these pictures are more complex, a unique deep CNN has been developed to extract 256 significant characteristics for liver disease predictions utilizing the ultrasound images.

Fig. 3 shows the suggested CNN model. The suggested CNN model consists of six convolutional layers, with batch normalization and a max-pooling layer applied after two successive convolutional layers. Because batch normalization re-centres and re-scales the layer inputs, it improves the model's stability and speed of operation. In between two consecutive convolutional layers, there is a pooling layer. The most important elements of the images may be extracted by using max-pooling with 2 × 2 filters, which choose the biggest value from each cluster's whole neuron at the convolutional layers. Since the output is determined through adding the filters to each image tuple, the "SAME" padding has been added to the first two convolutional layers. Because border components frequently include important properties, they have been examined. Zero padding was used in the computation of the border components. The border components, however, were disregarded by the 'VALID' padding.

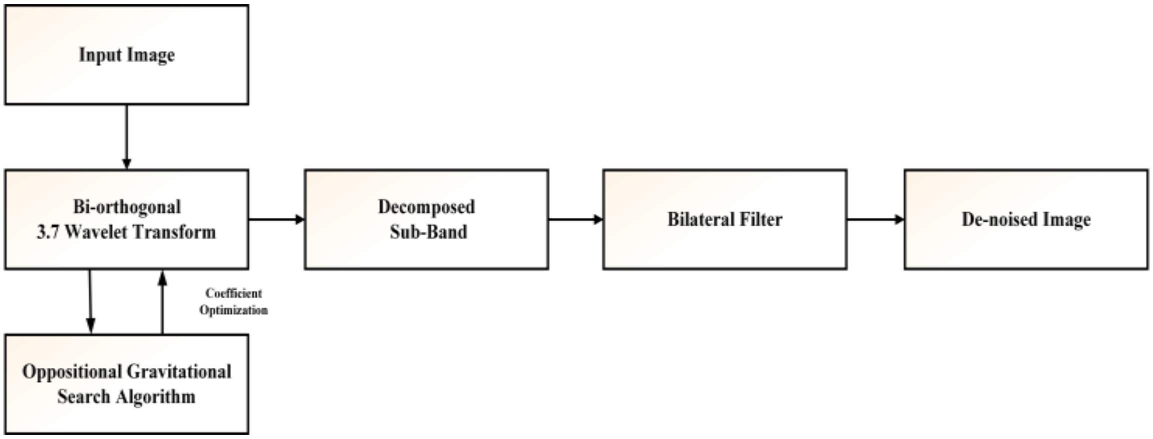

Fig. 2. Process of pre-processing.

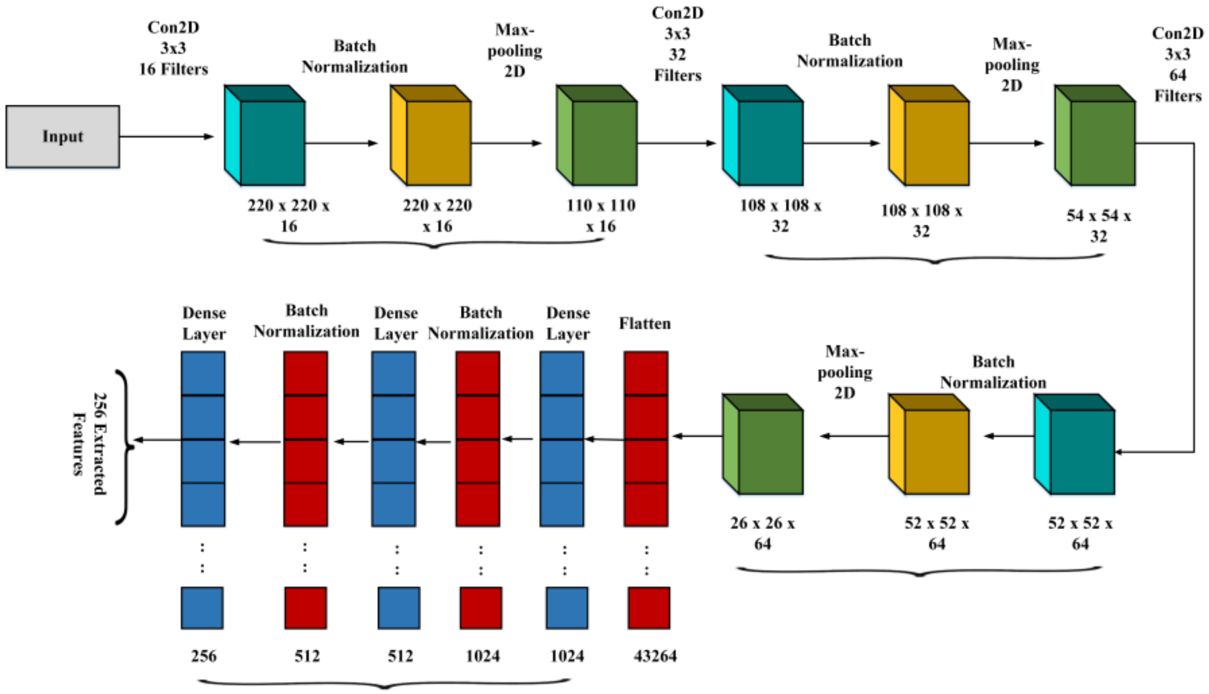

Fig. 3. Proposed CNN model.

ReLU has been used as an activation function in order to prevent the gradient from fading. There are two dropout layers that have been employed, one after the initial fully connected layer and the other after the last max-pooling layer. Both dropout layers have a probability of 0.5. Here, the training time increases significantly by using the dropout layers to reduce overfitting by frequently not training every node in every layer during the training stage. Because the Adam optimizer operates better while training on huge quantities of information and is extremely accurate for CNNs, it has been selected. Lastly, the 512 discriminant characteristics from each picture have been extracted using the final dense layer.

2) Classification using extreme learning machine: A feed-forward neural network with a number of layers of concealed nodes is called an ELM, and is typically used for pattern learning, regression, clustering, small estimate, compression as well, and categorization. It does not require the adjustment of hidden node variables, such as biases and weights. Conversely, the characteristics of hidden nodes can be transmitted down from their ancestors without modification, or they can be assigned at random and never altered. Comparing these models to networks trained using backpropagation, they learn far more quickly. In feed-forward neural networks, the learning process that is most frequently employed is backpropagation, which allows gradients to propagate from the output to the input. Backpropagation, however, has a lot of issues. In most applications, the training procedure takes an extended amount of time since biases and weights must be justified after each iteration. This approach ignores the weight magnitude in order to obtain maximum accuracy, which leads to decreased output over time. The update of weights and biases is no longer a barrier as a result of ELM, a feed-forward network. In order to maximize this model's overall effectiveness, it additionally concentrates on obtaining the lowest weight requirements in addition to the least training error. Simple alternatives are used for addressing the challenge of catching in local minima, hence eliminating such insignificant problems. Fig. 4 shows how ELM functions.

Let S be the arbitrary samples(q_i, r_i), and let $q_i = [q_{i1}, q_{i2}, \dots \dots q_{im}]^R \in P^m$ and $r_i = [r_{i1}, r_{i2}, \dots \dots r_{in}]^R \in P^n$, the standard single- concealed layer feedforward neural networks (SLFNs) with H concealed nodes and an activation function $f\ (\cdot)$ is expressed using Equation (1).

$$\sum_{u=1}^{H} w_u f_u(q_v) = \sum_{u=1}^{H} w_u f(b_u \times q_v + d_u) = o_v, (v = 1,2, \dots S) \qquad (1)$$

In this case, $b_i = [a_{i1}, a_{i2}, \dots \dots a_{im}]^R$ and $w_i = [w_{i1}, w_{i2}, \dots \dots w_{im}]^T$ is the weight vector that connects the u^{th} concealed node to the input nodes.d_i is the hidden node threshold, and $o_v = [o_{v1}, o_{v2}, \dots \dots o_{vm}]^R$ is the weight vector connecting the i^{th} concealed node to the output node. R is an example of an SLFN's v^{th} output vector.

Standard SLFNs with H concealed nodes and activation function $f\ \ (\cdot)$ can estimate these R illustrations with zero error, which means that $\sum_{v=1}^{H} \|o_v - r_v\| = 0$ and that there exist $\omega_u, b_i, and\ d_r$ such that

Using H hidden nodes and an activation function of $f\ (\cdot)$, standard SLFNs can calculate these R representations with zero error. This implies that $\sum_{v=1}^{H} \|o_v - r_v\| = 0$ and that $\omega_u, b_i, and\ d_r$ exist and it is given in Equation (2).

$$\sum_{v=1}^{H} w_u f(b_u \times q_v + d_u) = r_v, (v = 1,2, \dots S) \qquad (2)$$

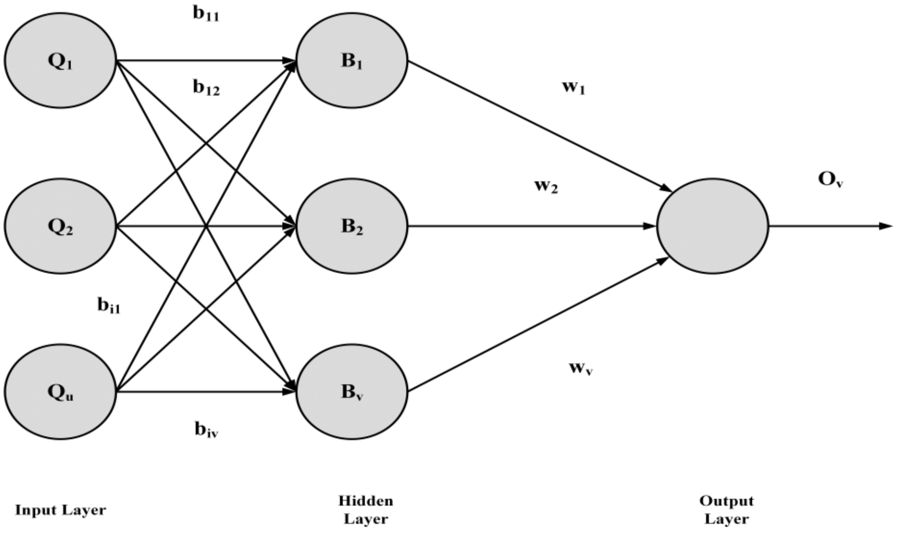

Fig. 4. Working of extreme learning machine

Equation (3), (4), (5) and (6) is an expanded version of the equation mentioned previously.

$$Nw = R \tag{3}$$

Where Equation (4),

$$N(a_1, \dots, a_H, d_1, \dots, d_H, x_1, \dots, x_H) = \begin{bmatrix} f(b_1 \times x_1 + d_1) & \dots & f(b_H \times x_1 + d_H) \\ \vdots & \dots & \vdots \\ f(b_1 \times x_S + d_1) & \dots & f(b_H \times q_S + d_H) \end{bmatrix}_{S \times H} \tag{4}$$

$$w = \begin{bmatrix} w_1^R \\ \vdots \\ . \\ w_M^R \end{bmatrix}_{H \times m} \tag{5}$$

$$R = \begin{bmatrix} r_1^R \\ \vdots \\ . \\ r_M^R \end{bmatrix}_{H \times m} \tag{6}$$

Where, the j^{th} column of N represents the outcome of the j^{th} hidden node based on inputs$x_1, x_2, \dots \dots x_S$, and N is referred to as a matrix of outputs of hidden layer. The linear technique's solution is given in Equation (7).

$$w = N^{-1}R \tag{7}$$

Where, the Moore–Penrose extended inverse of matrix N is denoted by N^{-1}.

Equation (8) defines the ELM's output function.

$$h(x) = q(x)w = q(x)N^{-1}R \tag{8}$$

3) Hybrid CNN-ELM algorithm: The Hybrid CNN-ELM technique combines the strengths of Extreme Learning Machine (ELM) for effective classification and Convolutional Neural Network (CNN) for reliable feature extraction from liver disease-related data. The combination of the CNN-ELM model improves liver disease prediction accuracy by combining CNN's effective visual feature extraction with ELM's fast learning. Its benefits include increased accuracy, faster learning, and more sensitivity, demonstrating efficiency in making exact predictions for liver illness and excellent performance and dependability. By giving a thorough method for identifying relevant characteristics and correctly categorizing liver disease a prerequisite for successful medical intervention this integration improves prognosis accuracy. Fig. 5 below provides a representation of the CNN-ELM hybrid algorithm. CNN and ELM are the two primary designs; CNN was once a characteristic extractor and ELM was a classifier. A single convolutional layer and a single pooling layer constitute the suggested CNN architecture. The study needs one hidden layer for the ELM, which is located between the input and output layers.

The image that reaches the convolutional layer is the first step in the CNN-ELM's main flow. Next, the image matrix that ReLU activates enters the pooling layer. Every processed image matrix then became a one-dimensional vector that could be entered into the ELM's input layer. The neural network uses a generic computation to generate the flattened image information before it enters the ELM concealed layer and is stimulated by the sigmoid function. Following the activation of values, the procedure proceeds to calculate the ELM from the layer that is concealed to the output layer, utilizing the following formula to obtain the categorization outcome, which is Equation (9).

$$W_{s-0} = (Y^R Y)^{-1} Y^R x \tag{9}$$

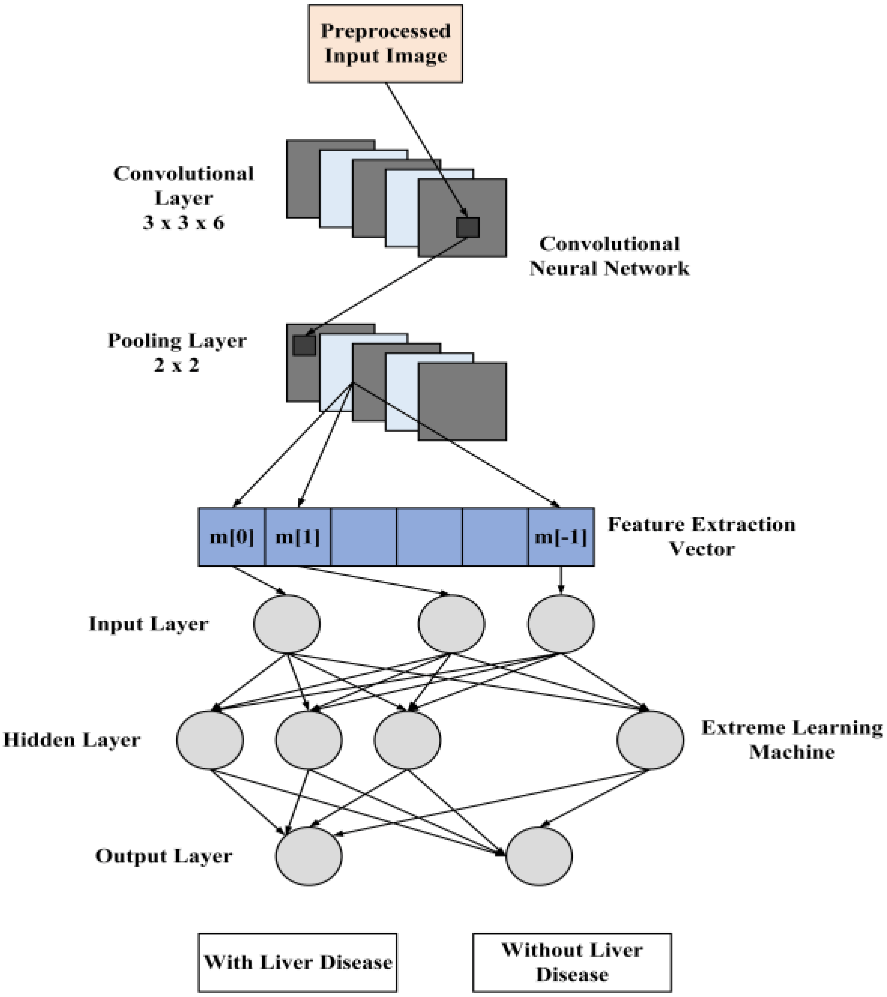

Fig. 5. CNN-ELM hybrid structure.

D. Grey Wolf Optimization Framework for Fine-tuning the Parameters

The Grey Wolf Optimization (GWO) framework optimizes the Convolutional Neural Network (CNN) and Extreme Learning Machine (ELM) components by fine-tuning parameters post-Hybrid CNN-ELM algorithm. Through appropriate parameter modifications in the feature extraction and classification process, the model is gradually enhanced for a better prognosis of liver illness, imitating the hunting behaviours of grey wolves. This iterative technique also improves accuracy. The GWO algorithm mimics the wolf's approach to hunting, which consists of circling the target and working together to make selections. Specifically, GWO is used to improve model hyperparameters including regularization factors, network design, and learning rates when it comes to parameter modifications. Two primary stages comprise the implementation of GWO in this hybrid CNN-ELM architecture. The CNN's architecture and hyperparameters, such as the number of convolutional layers, filter sizes, and learning rates, are first optimized using GWO. This ensures that pertinent characteristics are efficiently extracted from the ultrasound images by the CNN. The ELM model's hyperparameters, including the quantity of hidden nodes, activation functions, and regularization terms, are then adjusted using GWO. Through methodical parameter space exploration and utilizing wolves' cooperative decision-making approach, GWO assists in setting the system's feature extraction (CNN) and categorization (ELM) components, resulting in improved prediction accuracy for diseases of the liver.

GWO, a meta heuristic technique, was proposed [23]. The killing tactic and pack organization of grey wolves had an impact on the technique. Grey wolves live in packs and have an exceptionally hierarchical culture. Decision-making has been handed over to the alphas (α), the wolves' rulers. Alpha wolves are assisted in their tasks by beta (β) wolves, who fall within the following level. The victim in this system is the last individual, known as Omega (ω). If a wolf does not fit into any of the above-mentioned classifications, it is occasionally referred to as a delta (δ) wolf. In line with this well-defined hierarchy, grey wolves try to encircle a food supply, attack, and kill, then search for other prey. The way that wolves hunt is defined as follows: (i) a way to enclose prey; (ii) a way to locate and kill animals; and (iii) a way to battle a prey. Equations (10) and (11) describe how grey wolves circle their prey during a hunting expedition.

$$\vec{K} = \left|\vec{f} \cdot (\overrightarrow{X_w}(n) - \vec{X}(n)\right| \tag{10}$$

$$\vec{X}(n+1) = \overrightarrow{X_w}(n) - \vec{Q} \cdot \vec{K} \tag{11}$$

Where $\vec{X}$ depicts wolf's location in round configuration; $\overrightarrow{X_w}$is the prey's vector position; n is present time; $\vec{Q}$ and $\vec{K}$ are effective vectors that have the following definitions is shown in Equation (12) and (13).

Equations (12) and (13), where $\vec{X}$ represents the wolf's location in a circular configuration, $\overrightarrow{X_w}$ represents the prey's vector position, n denotes the current time, and $\vec{Q}$ and $\vec{K}$ represent effective vectors with the corresponding definitions.

$$\vec{Q} = 2\vec{p} \cdot \overrightarrow{c_1} - \vec{p} \tag{12}$$

$$\vec{f} = 2 \cdot \overrightarrow{c_2} \tag{13}$$

Random vectors equally distributed between 0 and 1 are included in $\overrightarrow{c_1}$ and $\overrightarrow{c_2}$ where the element d is progressively decreased from 2 to 0. The $\alpha, \beta, and\ \delta$ wolves are thought to comprehend it better since the location of the meal is never evident in advance. Equations (14), (15), and (16) are used to determine the victim's location by utilizing the wolves' positions.

$$\vec{K}_\alpha = \left|\vec{f}_1 \cdot \vec{X}_\alpha - \vec{X}\right|,\ \vec{K}_\beta = \left|\vec{f}_2 \cdot \vec{X}_\beta - \vec{X}\right|,\ \vec{K}_\delta = \left|\vec{f}_3 \cdot \vec{X}_\delta - \vec{X}\right| \tag{14}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{Q}_1 \cdot \vec{X}_\alpha,\ \vec{X}_2 = \vec{X}_\beta - \vec{Q}_2 \cdot \vec{K}_\beta,\ \vec{X}_3 = \vec{X}_\delta - \vec{Q}_3 \cdot \vec{K}_\delta \tag{15}$$

$$\vec{X}(n+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{16}$$

Assuming the study have an estimated position, the next step is to stalk the victim (exploitation). Since the condition of wolves grows closer to the prey's site as p in Equation (11) lowers from 2 to 0, the vector $\vec{Q}$ can be employed to achieve this purpose. Furthermore, variables f and Q both help preserve the method's exploring capabilities intact while eliminating the need for local averages. The variable f can change the location of food and the challenge of foraging, but it can also have an impact on a Q value greater than one, that is, $|Q| > 1$ which forces the wolves to stray from their food and seek it out. After applying the approach to a pack of wolves for a predetermined number of repetitions, Equation (13) will eventually show the location of the prey or the best area in the globe.

Grey Wolf Optimization (GWO) works in collaboration with Extreme Learning Machine (ELM) and Convolutional Neural Network (CNN) to forecast liver illness. GWO refines ELM and CNN hyperparameters by utilizing grey wolf searching algorithms. This two-stage optimization technique gradually increases the model's accuracy. By combining the capabilities of ELM along with CNN and GWO, the unified system of CNN-ELM-GWO obtains improved precision in liver disease categorization. The cooperative approach collaboration of GWO improves the model's resilience, allowing for effective adjustment and optimization, ultimately improving the system's overall effectiveness in forecasting.

V. Results and Discussion

The findings of the suggested method have been addressed in this section. A comprehensive process for predicting liver disease utilizing a collection of liver ultrasound images constitutes a component of the methodology used in this investigation. Preprocessing is done employing a hybrid approach that combines bilateral filtering and optimal wavelet transformation to minimize noise and increase the resolution of the image. Then, a CNN with six convolutional layers, batch normalization, and max pooling was developed in order to obtain important information from the ultrasound images. 256 discriminant features were generated for the prediction of liver disease employing this CNN as the feature extractor. These features were then added to the machine for classification in order to utilize an ELM enhanced learning speed and non-adjustable hidden node settings. The hybrid CNN-ELM technique enhances accuracy by fusing the feature extraction and classification procedures. Finally, the GWO approach was used to modify the hyperparameters of the CNN and ELM models in order to further improve the system's efficacy. This comprehensive approach forecasts liver disease accurately by combining deep learning, metaheuristic optimization and advanced image processing.

A. *Performance Evaluation*

Evaluation metrics are crucial for evaluating categorization performance. The method that is most frequently used for this is an accuracy measurement. The accuracy of a classifier for a given dataset may be determined by looking at the proportion of testing datasets that it properly classifies. Since selecting the best decisions is not possible simply by using the accuracy measure. Researchers also used a few more criteria to assess the classifier's effectiveness. Metrics including F1-score, accuracy, recall, and precision were utilized to evaluate the efficacy of the suggested approach. The following is a description of each measure's definition:

T_{pos} (True Positive) is used to describe the amount of information that has been effectively categorized.

The term $Fpos$ (False Positive) explains the amount of accurate information that was incorrectly categorized.

False negatives (F_{neg}) are situations where inaccurate information has been categorized as authentic.

The erroneous information values are categorized and referenced to as T_{neg} (True Negative).

1) Accuracy: The classifier's accuracy indicates how frequently it arrives at an appropriate conclusion. The ratio of accurate estimates to all other possible possibilities is known as accuracy. It is demonstrated by Equation (17).

$$Accuracy = \frac{T_{pos} + T_{neg}}{T_{pos} + T_{neg} + F_{pos} + F_{neg}} \tag{17}$$

2) Precision: The precision, or level of accuracy, of a classifier is employed to determine how many results are correctly classified. While lower precision results in many more false positives, higher accuracy reduces the number of false positives. The percentage of instances correctly assigned to all occurrences is known as precision. It is defined by Equation (18).

$$P = \frac{Tpos}{Tpos+Fpos} \tag{18}$$

3) Recall: The recall of a categorization defines its sensitivity, or the amount of pertinent information it produces. The overall amount of $Fneg$ is reduced through recall enhancement. The concept of recall is the ratio of correctly identified cases to the entire number of expected occurrences. This is demonstrable by Equation (19).

$$R = \frac{Tpos}{Tpos+Fneg} \tag{19}$$

4) F1-Score: The F1-Score, which is the weighted mean of recall and accuracy, is the result of combining recall and precision measures. It is characterised by Equation (20).

$$F1\ measure = \frac{2\times precision \times recall}{precision\times recall} \tag{20}$$

5) ROC Curve: In deep learning and machine learning, area under the ROC curve, or AUC, is a popular assessment statistic for binary categorization issues. The Area under the Curve (AOC) is a visual depiction of the Receiver Operating Characteristic (ROC) curve that shows how effective the binary recognition technique is. In a binary classified issue, the classifier determines whether the incoming data is part of a positive or negative division. The ROC curve displays the $Tpos$ vs. the F_{pos} for different categorization criteria. AOC values are between 0 and 1, where larger values indicate higher effectiveness. An optimum classifier has an AOC of one, whereas a totally randomized classifier has an AOC of 0.5. Since the approach takes into account every conceivable level of identification and provides just one statistic for comparing the effectiveness of various classifiers.

The training and testing accuracy levels of the suggested model throughout several training epochs are shown in Fig. 6. The model performed better and better during the course of 100 epochs of training. The training accuracy was 76.6% and the testing accuracy was 74.5% at the beginning, after only 10 epochs. However, training and testing accuracy levels steadily improved as the model learned and adjusted across additional training epochs. After 100 epochs of training, the model performed admirably, with a testing accuracy of 99.7% and a training accuracy of 99.3% towards the end of the procedure. With the testing accuracy showing the model's ability to produce correct predictions on data that has never been observed before and the training accuracy showing how well the model matches the training information, the graphic illustrates the model's capability to learn and generalize.

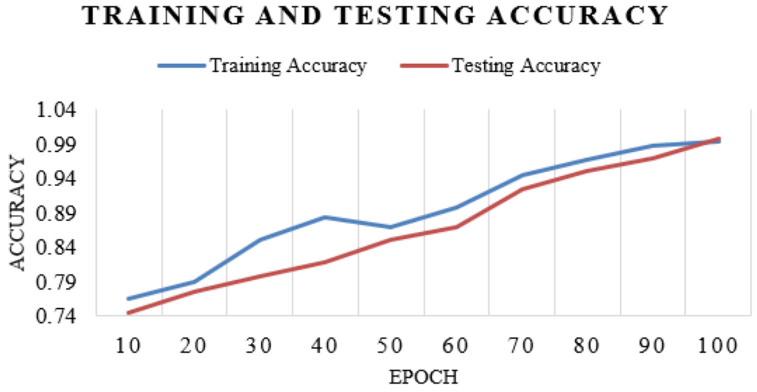

Fig. 6. Training and testing accuracy.

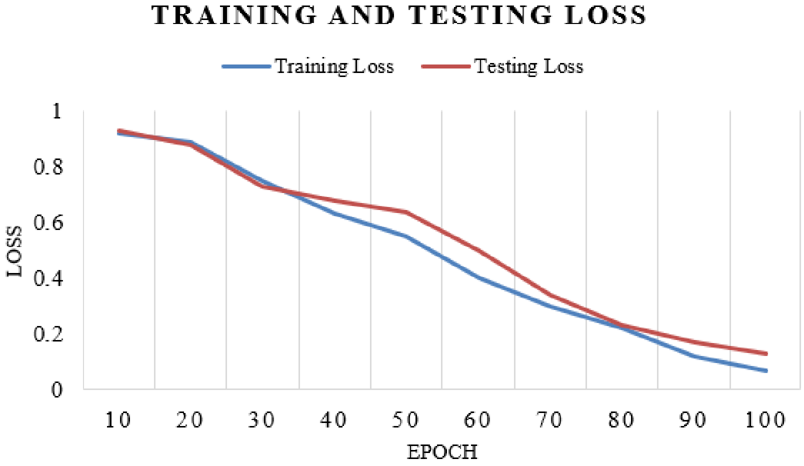

Fig. 7. Training and testing loss.

The suggested model's training and testing loss values are shown in Fig. 7 as it endures several training epochs. It displays the effectiveness of the model and its capacity to reduce mistake. The training loss was very significant at 0.92 at the start of training, with only 10 epochs, suggesting that the model's projections on the training information had a substantial margin of error. Concurrently, the testing loss was additionally slightly elevated at 0.93, indicating that the model did not perform much better on unobserved information. Training and testing losses reduced in an uninterrupted way as the model learned additional epochs, indicating that the model was getting better at generating predictions. The model reached low training and testing loss values of 0.07 and 0.13, respectively, towards the end of the training procedure, which lasted 100 epochs. These low loss values demonstrate the model's capacity to effectively decrease mistakes and generalize, since it has trained to generate extremely precise forecasts on both the training and testing datasets.

In terms of accuracy, precision, recall, and F1-Score for liver disease prediction, Table I and Fig. 8 provide a thorough comparison of the effectiveness of the proposed CNN-ELM-GWO method with other existing approaches, such as MLP (Multi-Layer Perceptron), RF (Random Forest), KNN (K-Nearest Neighbours), and NB (Naive Bayes). The outcomes show that the suggested CNN-ELM-GWO approach performs noticeably better than any other methods.

It demonstrates its capacity to provide incredibly precise forecasts by achieving an amazing accuracy of 99.7%. Additionally, the approach performs very well in terms of accuracy, recall, and F1-Score, all of which are continuously above 99%, indicating its resilience in accurately detecting liver disease cases. The conventional machine learning techniques, on the other hand, show consistently lower performance measures. These include MLP, RF, KNN, and NB. The table highlights the enhanced predictive capability of the suggested CNN-ELM-GWO technique, rendering it an exceptionally efficient and dependable solution for the categorization of liver illness.

The True Positive Rate and False Positive Rate for a binary classification model are shown at different threshold settings in Fig. 9. The fraction of real negative instances that the model mistakenly classifies as positive is represented by the False Positive Rate, which is displayed in the right column. The True Positive Rate shows the percentage of true positive cases that the model properly recognized. The True Positive Rate increases in conjunction with the incremental increase in the threshold from 0 to 0.6 for categorizing occurrences as positive, indicating enhanced sensitivity in accurately identifying positive situations. Concurrently, as the threshold gets more compressed more negative instances are mistakenly categorized as positive, according to the growing False Positive Rate. The relationship between True Positive and False Positive Rates at various categorization thresholds can potentially be evaluated using Fig. 9, which is a useful tool for choosing the best threshold for a particular categorization task.

TABLE I. COMPARISON OF PERFORMANCE OF PROPOSED METHOD WITH OTHER EXISTING APPROACHES

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
KNN [19]	62.90	56.60	55.80	56.19
NB [21]	69.20	70.15	60.16	64.53
MLP [16]	71.59	58.25	70.76	63.89
RF [17]	72.20	62.10	68.80	65.25
Proposed CNN-ELM-GWO	99.7	99.4	99.4	99.2

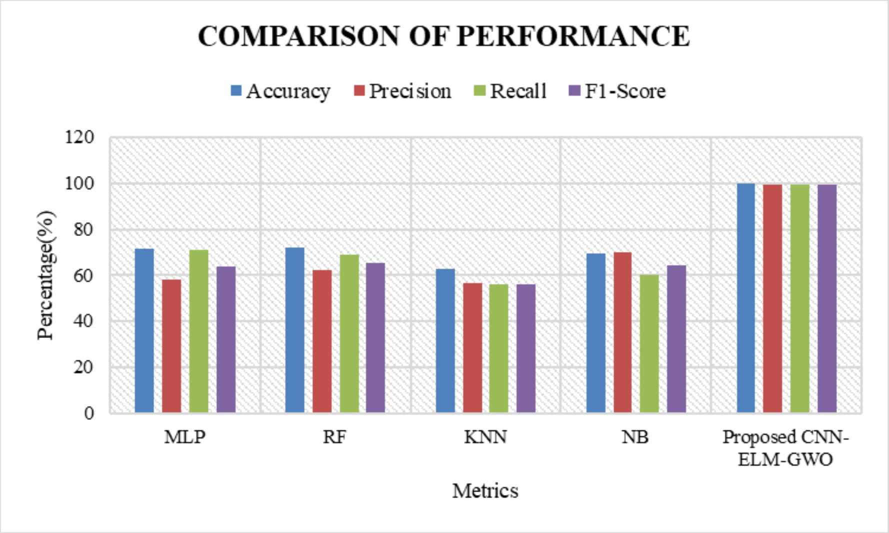

Fig. 8. Comparison of performance of proposed method with other existing approaches.

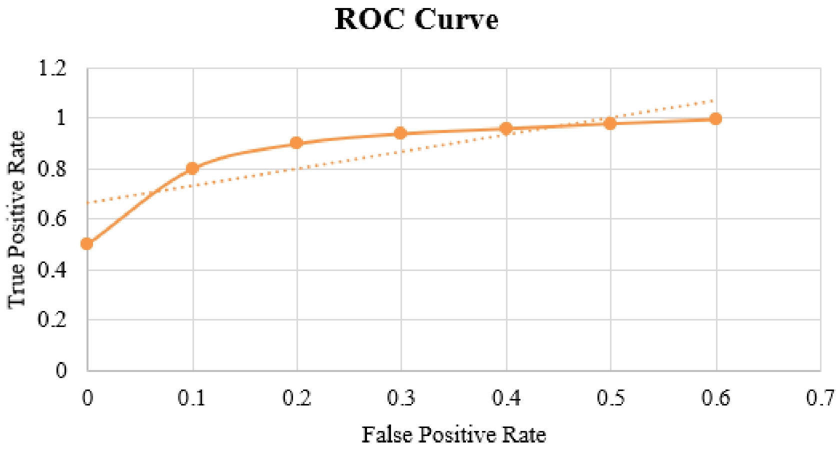

Fig. 9. ROC curve.

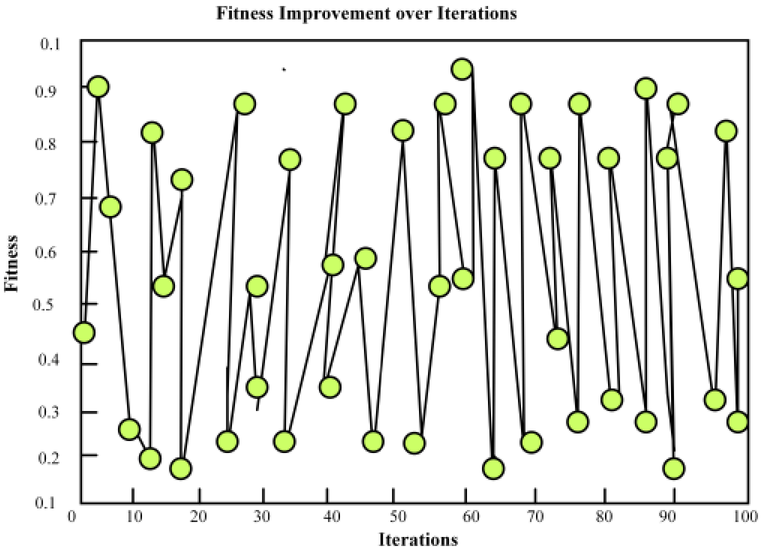

Fig. 10. Fitness improvement over iterations.

The progress of fitness improvement attained by the Grey Wolf Optimization method over several iterations is shown in Fig. 10 shows the Fitness Improvement over Iterations. It serves as an indication for how well the GWO algorithm improves its results over time. The y-axis denotes the fitness level of the algorithm's solutions, which is often a measure of how practically the algorithm's output is to the ideal or intended outcome. The x-axis shows the number of iterations or optimization cycles. The graph's decreasing pattern in fitness values as the iterations go on illustrates that the GWO algorithm is gradually improving and perfecting its solutions. While the decrease in fitness becomes lower in subsequent iterations, it indicates that achieving additional improvements is becoming more difficult.

The high decline in fitness early in the iterations shows that the algorithm is swiftly converging towards better solutions. This graph is crucial for assessing the effectiveness and pace of convergence of the GWO procedure. It also aids in deciding whether to stop the algorithm when the required level of fitness is attained.

A comprehensive evaluation of many datasets, including the Liver Disorder Dataset, Indian Liver Patient Dataset, and the Proposed Liver Ultrasound Images, is shown in Table II and Fig. 11 when compared to important performance metrics, such as accuracy, precision, recall, and F1-Score. The accuracy of the Liver Disorder Dataset was 70%, while the equivalent values for precision, recall, and F1-Score were 68%, 68%, and 69%, respectively. On the other hand, the Indian Liver Patient Dataset performed better, scoring 81% in terms of F1-Score, precision, and recall, and 80% in terms of accuracy. The suggested Liver Ultrasound Images dataset performed significantly superior to the others, with high values for precision, recall, and F1-Score (99.4%, 99.2%, and 99.7%, respectively). In comparison to current datasets, the proposed results demonstrate the higher predictive capabilities of the proposed technique when applied to Liver Ultrasound Images, indicating its potential as a diagnostic tool for liver illness.

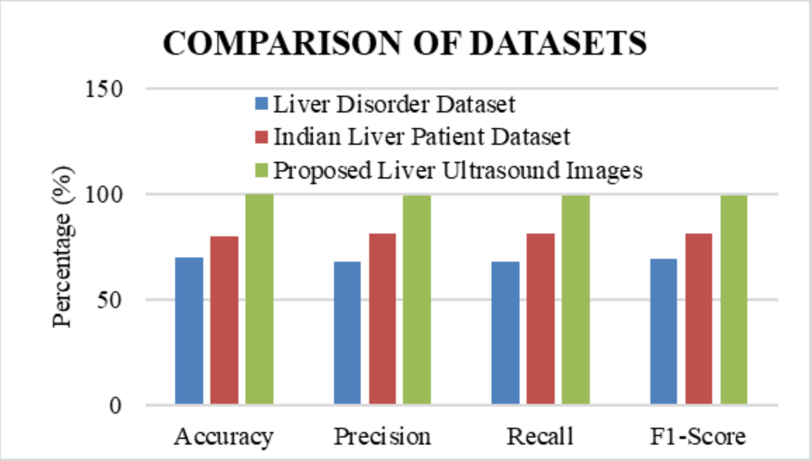

Fig. 11. Comparison of datasets of proposed method with other existing approaches.

TABLE II. COMPARISON OF DATASETS OF PROPOSED METHOD WITH OTHER EXISTING APPROACHES

Datasets	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Liver Disorder Dataset	70	68	68	69
Indian Liver Patient Dataset	80	81	81	81
Proposed Liver Ultrasound Images	99.7	99.4	99.4	99.2

B. Discussion

The suggested liver disease prediction approach uses sophisticated preprocessing, bilateral filtering, and effective wavelet transformation to improve picture quality. When used with an ELM, a six-layer CNN retrieves 256 discriminant features, which optimizes learning. GWO improves the model's efficacy through hyperparameter tweaking. Evaluation measures show remarkable results, with 99.3% along with 99.7% accuracy in testing as well as training, respectively. Traditional constraints in liver disease forecasting include poor accessibility within artificial neural networks, feasible prejudices in dataset depiction, and the difficulty of current time application [20]. The CNN-ELM-GWO method surpasses previous approaches in a comparative analysis, demonstrating its dependability for liver disease categorization. Fitness Improvement across Iterations as well as ROC curve evaluations validate the model's effectiveness and convergence rate. This integrated technique shows potential for reliable liver disease prediction, outperforming alternative approaches. Despite its efficacy, the suggested liver disease prediction approach is limited. The dependence on ultrasound pictures may restrict applicability to other types of imaging. The model's effectiveness may be impacted by the dataset's consistency from a single medical institute. Furthermore, the substantial computational of the CNN-ELM-GWO method may provide difficulties for real-time applications. Further validation on varied datasets, as well as consideration of computing efficiency, are critical to assuring the method's broad application and usefulness. Future research should focus on improving the liver disease forecasting model. Exploring varied datasets collected by various medical institutes will result in greater application. Integrating with additional imaging modalities may increase generalization. Reducing computational complexity will improve real-time application practicality. Investigating interpretability and adding specific patient information might improve customized treatment techniques. Validation in clinical settings, as well as collaboration with healthcare experts, will help to make the model more practical, increasing its influence on liver disease detection and treatment.

VI. CONCLUSION AND FUTURE WORK

This study proposes a unique technique for identifying liver disease based on ultrasound images that takes advantage of the combined abilities of an integrated CNN-ELM-GWO model. The proposed technique surpasses standard machine learning methods with an incredible 99.7% accuracy, emphasizing the critical need for rapid and precise detection of liver disease, which is critical for effective patient treatment. The model provides an effective and innovative architecture by combining an Extreme Learning Machine for classification, a Convolutional Neural Network for feature extraction, and Grey Wolf Optimization for hyperparameter tuning. The CNN-ELM-GWO model's outstanding accuracy emphasizes the need for early detection, which is required for immediate treatment. This result may influence future research that employs advanced algorithms based on machine learning to enhance the identification of various illnesses, advancing the area of medical image evaluation. The findings motivate more research and advocate for more extensive deployment and development of the approach, which ought to result in improved patient outcomes and more informed healthcare decisions. Future research paths might include merging CT or MRI images alongside other types of imaging to increase diagnostic accuracy. Predictions might be made more personalized by using patient-specific information and medical history. The model's practical use would be enhanced if bigger, more diverse datasets were employed for assessment and practical clinical application. Obtaining credibility and adoption of the proposed technique by healthcare professionals necessitates exploring interpretability alternatives for the model's findings. Future research should focus on expanding the dataset to increase model generalization across different populations and medical circumstances. Furthermore, for practical significance, ongoing capability and incorporation into clinical processes must be studied. Improving the CNN-ELM-GWO model's comprehension and removing any biases will assist healthcare professionals in accepting and believing in it.

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Personalized Recommendation Algorithm Based on Trajectory Mining Model in Intelligent Travel Route Planning

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***Abstract*—With the increasing demand for personalized travel, traditional travel route planning methods are no longer able to meet the diverse needs of users. In view of this, on the ground of the analysis of user trajectory data at the temporal and spatial levels, a new scenic spot recommendation model is proposed by combining personalized recommendation algorithms. Meanwhile, improved genetic algorithm and minimum spanning tree algorithm were introduced to adjust the structure of the personalized recommendation model. After matching the visit sequence of scenic spots, the final new personalized tourism route recommendation model was proposed. The experiment demonstrates that the optimal pause time for the personalized scenic spot recommendation model is 45 minutes, the pause distance is 15 meters, and the clustering radius is 500 meters. And the model has the highest accuracy in the Tok-10 testing environment, with a maximum value of 90%. In addition, the new personalized tourism route recommendation model has the highest accuracy of 85.6%, the highest recall rate of 88.7%, the highest F1 value of 92.4%, and an average convergence rate of 88.9%. In summary, the new scenic spot and route recommendation model proposed in the study can achieve more intelligent and personalized travel route planning, providing new guidance for the intelligent development of travel route recommendation.**

***Keywords*—Trajectory mining; personalized recommendations; travel routes; genetic algorithm; visiting sequence of scenic spots**

I. INTRODUCTION

As the boost of intelligent technology and people's increasing pursuit of personalized experiences, personalized recommendations have become an indispensable part of smart travel route planning to enhance the travel experience of travelers [1]. Many domestic and foreign researchers have conducted varying degrees of exploration to address the problems in this field. And relevant researchers have successively developed route planning techniques using global positioning systems and geographic information systems, and proposed personalized recommendation models for travel route planning [2]. These technical models can to some extent meet the line planning requirements of users. But with the diversification of demand, these technologies have also exposed issues such as slow real-time performance, poor accuracy, and low interactivity [3]. With the continuous development of trajectory mining technology, it is widely used in location services, logistics management, and other areas due to its superior real-time data monitoring and efficient data-driven characteristics [4]. In view of this, the study attempts to innovatively introduce user data trajectory mining technology on the basis of existing personalized recommendation algorithms. By analyzing the trajectory changes of users in time and space and adjusting the structure of recommendation algorithms, a new intelligent travel route planning model can be achieved. The rationale for this initiative lies in the lack of solutions in the current market that can provide personalized travel advice by taking into account users' historical behavioral data and real-time location information. Its significance is reflected in its ability to greatly enhance the user's travel experience and plan more personalized and reasonable travel routes for travelers through intelligent data analysis. The core research questions and objectives are closely centered on how to effectively use trajectory mining techniques to achieve personalized recommendations, as well as to improve algorithms to optimize the structure of the recommendation model to improve the accuracy and applicability of real-world travel planning. This directly addresses the core challenges in the field of intelligent travel planning, such as dealing with large spatio-temporal datasets and providing personalized travel recommendations that match user needs. The study first outlines the progress and limitations of related research and clarifies the research objectives. Then, the process of constructing a personalized recommendation model based on spatio-temporal trajectories is introduced. The validity of the model is verified through experiments. Finally, the research results are summarized, its application in the field of smart travel planning is discussed, and future research directions are proposed.

II. RELATED WORKS

With the continuous development of technology, intelligence has penetrated into every aspect of people's lives, and the travel industry is no exception. Yao Z et al. found that existing tourism route planning techniques have lower planning accuracy when facing complex environments. In view of this, the research team proposed a new travel route map matching method by combining mobile phone trajectory switching data under 5G networks. The experiment demonstrates that this method has high accuracy in planning user travel routes, and can switch to view parallel roads with smaller spacing at any time through mobile phones [5]. Huang F et al. found that existing travel route planning methods mainly focus on single planning problems for specific tasks, but cannot be applied to other tasks. In view of this, the research team proposed a multi task deep travel route planning framework by combining interest attributes, user preferences, and historical route data. The experimental results show that the framework is more effective in general path planning compared to similar planning methods and better meets user needs [6]. Khamsing N et al. proposed a novel optimal decision model for family tourism route planning by combining adaptive large neighborhood search method to explore the optimal solution in daily family tourism route planning problems. The experiment demonstrates that the average total travel cost of the optimal route under this decision model is relatively low, and the average travel satisfaction is 89% [7]. Zhu S proposed a multi-objective mixed linear programming model for circular tourism to maximize the utilization of tourist attractions by cyclists and minimize the total travel time by combining multi-objective algorithms. The experiment demonstrates that the model can continuously update the optimal path plan in actual bicycle tourism path planning, greatly increasing the service level of bicycle tourism path planning [8].

With the development of position sensing technology and the popularization of smart devices, the acquisition of trajectory data has become easier. The application fields of trajectory mining technology are also becoming increasingly widespread. To achieve accurate prediction of flight delays, Shao W et al. proposed a flight prediction model combining trajectory mining technology by utilizing various vehicle trajectories and related sensor data on the airport apron. The experimental results show that the error rate of the test results of the model in the simulation environment is only 2.56% [9]. Jiang L et al. found that when trajectory data shows low quality, the map matching effect cannot achieve satisfactory results. In view of this, the research team proposed a trajectory data augmentation technique that combines deep learning. The experiment demonstrates that this technology, with its superior migration mode and high-quality trajectory data expression, performs far better than other data augmentation models of the same type. With the rapid development of the Internet and the explosive growth of information, users often feel confused and anxious when facing massive amounts of information. The emergence of personalized recommendation algorithms provides an effective solution to this problem [10]. Chen et al. found that users find it difficult to find resources of interest in large capacity interactive calligraphy experience devices. In view of this, the research team proposed a hybrid personalized recommendation algorithm that combines content and coordinated filtering. The experiment demonstrates that the algorithm can accurately predict user selection, demonstrating certain effectiveness and superiority [11]. Zou F et al. found that traditional recommendation systems only ensure the accuracy of recommendations and lose the diversity of recommendations. In view of this, the research team proposed a two-stage recommendation algorithm that combines collaborative filtering (CF) and multi-objective teaching decomposition. The experiment demonstrates that this method is highly effective and efficient on the Movielens dataset [12].

In summary, although the previous studies have made progress in the field of smart travel planning, they mainly focus on static user preferences and do not sufficiently consider the complexity of spatio-temporal data, resulting in the inability to accurately capture users' real-time behaviors. In addition, traditional recommendation algorithms suffer from inefficiency when dealing with large-scale spatio-temporal trajectory data. And the study proposes a personalized recommendation algorithm using trajectory mining aims to address these limitations. By deeply analyzing users' spatio-temporal trajectory data, the algorithm can dynamically capture changes in user preferences. Combining the improved genetic algorithm and the minimum spanning tree algorithm, the study optimizes the recommendation structure, enhances the planning efficiency and accuracy, and achieves intelligent and personalized travel route planning, overcoming the key gaps in existing research.

III. Construction of a Smart Travel Route Planning Model Combining Trajectory Model and Personalized Recommendation Algorithm

To improve the overall performance of the final smart travel route planning model, this study first mined user trajectory data and obtained a recommendation model for the user's target attractions through personalized algorithm data analysis. Secondly, on the ground of the personalized attraction recommendation model, improvements were made and the final personalized intelligent travel route planning model was proposed.

A. *Construction of Personalized Recommendation Model on the Ground of Spatiotemporal Trajectory*

In this era of information explosion, personalized recommendations have become an important way for the public to obtain information and enjoy services [13]. Data mining is nothing but the best personalized recommendation method, among which web scraping technology is the most classic. This technology simulates browser behavior by writing programs to automatically obtain information on the Internet. The working steps are shown in Fig. 1.

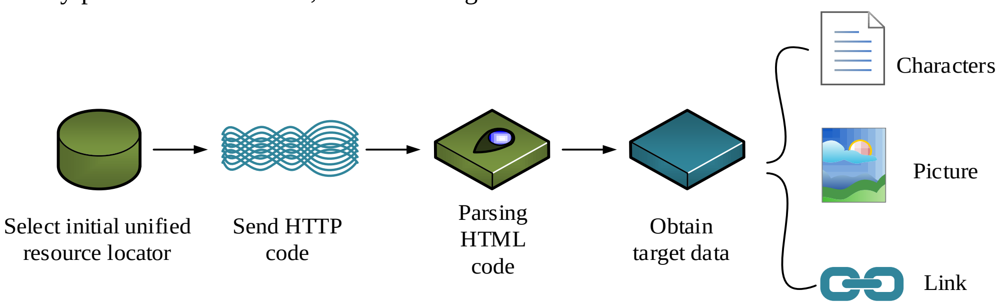


Fig. 1. Crawler technology workflow.

As shown in Fig. 1, the process of web crawling technology can be roughly divided into four steps. That is, sending HTTP code requests, parsing HTML code, extracting target data and storing it in the database. After completing the data crawler, the spatiotemporal trajectory analysis algorithm can analyze the user's temporal and spatial data, thereby strengthening the preference judgment of the user's historical data. The general spatiotemporal trajectory analysis uses Euclidean distance as a measurement unit to determine two similar data objects [14]. For different time nodes on two trajectories, it calculates the corresponding Euclidean distance meanwhile. The calculation formula for this process is shown in Eq. (1).

$$Dist(P,Q)=\sum_{i=1}^{n} dist(p_i,q_i) \tag{1}$$

In equation (1), p_i and q_i represent the nodes on the p and q trajectories at time point i, respectively, and n represents the total time point. The specific calculation of $dist(p_i,q_i)$ is shown in Eq. (2).

$$dist(p_i,q_i)=\sqrt{(p_{ix}-q_{ix})^2+(p_{iy}-q_{iy})^2} \tag{2}$$

In equation (2), (p_{ix},p_{iy}) represents the two-dimensional coordinates of node p_i, and (q_{ix},q_{iy}) represents the two-dimensional coordinates of node q_i. For the convenience of analysis, the Euclidean distance is converted into similarity calculation, as shown in Eq. (3).

$$sim(P,Q)=1-\frac{Dist(P,Q)}{\min(m,n)} \tag{3}$$

In equation (3), m and n represent the length values of trajectories p and q. Therefore, the similarity value interval after conversion can be determined as $(0,1)$, and the larger the value, the greater the similarity between the two trajectories. However, when faced with relatively large computational data, spatiotemporal trajectory analysis algorithms still face certain challenges. Therefore, the study focuses on scenic spots as recommendation objects and introduces the Mean Shift clustering algorithm to construct the user core access matrix [15]. It takes the location and time of each user's stay as a pause point, and after connecting all the pause points, it generates the user's travel path. The reasoning process of the pause point is shown in Eq. (4).

$$\begin{cases} L_i=\{l_1,l_2,l_3,\cdots,\mathrm{l_n}\} \\ \mathrm{l_n}=\{long_n,latt_n\} \end{cases} \tag{4}$$

In equation (4), L_i represents all pause records of the user, and $\mathrm{l_n}$ represents the pause location at time n. $long_n$ and $latt_n$ represent the longitude and latitude of the pause point, respectively. To avoid the calculation of the maximum number of nearest pause points, the study first excludes pause points for users with shorter time and distance, as shown in Eq. (5).

$$\begin{cases} \min long_s=\frac{1}{s}\sum_{i=1}^{s} long_i \\ \min latt_s=\frac{1}{s}\sum_{i=1}^{s} latt_i \end{cases} \tag{5}$$

In equation (5), s represents all pause points of shorter time and shorter distance. After excluding these pause points, the corresponding clustering labels are established using the Mean Shift clustering algorithm, and a user core access matrix is constructed [16]. The process of this matrix is shown in the Fig. 2.

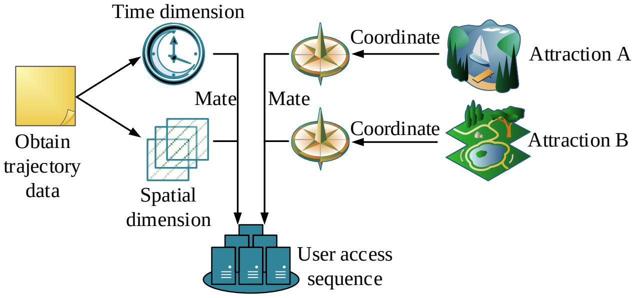


Fig. 2. User core access matrix flow.

As shown in Fig. 2, it first collects user access data and performs pause point analysis. It then establishes clustering labels for pause data in both temporal and spatial dimensions. In addition, it establishes a dataset of urban tourist attractions and classifies them through longitude and latitude coordinates [17]. Finally, it matches the pause data points after the label with tourist attractions, and the user access point at this point is the target point. It assumes that the vector of any point in the d-dimensional space after Mean Shift offset is shown in Eq. (6).

$$\begin{cases} M_h(x)=\frac{1}{k}\sum_{x_i\in S_h}(x_i-x) \\ S_h(x)=\{y\,|(y-x)(y-x)^T\le h^2\} \end{cases} \tag{6}$$

In equation (6), x_i is the i-th point, x represents any point, S_h is a low latitude sphere with a radius of h, T represents the number of iterations, and k represents the convergence center value. The entire algorithm obtains the final position that stabilizes the sphere by continuously approximating the offset vector towards any point x. The vector representation of the optimal point position at this time is shown in Eq. (7).

$$M_h(x)=\frac{\sum_{i=1}^{n} G(\frac{x_i-h}{h_i})w(x_i)(x_i-x)}{\sum_{i=1}^{n}\sum_{i=1}^{n} G(\frac{x_i-h}{h_i})w(x_i)} \tag{7}$$

In Eq. (7), h represents an element in a positive definite diagonal matrix, and h_i represents an element. $w(x_i)$ represents sample weight, $G(x)$ represents unit kernel function. To match the format of label data for the established visit sequence of scenic spots, the study abstracts any scenic spot, and the expression for this process is shown in Eq. (8).

$$\begin{cases} latt_{x`} \le latt_l \le latt_{y`} \\ long_{y`} \le long_l \le long_{x`} \end{cases} \tag{8}$$

In Eq. (8), l represents any pause point, and $(x`, y`)$ represents the coordinates of any scenic spot S_i. If the coordinate interval of the pause point is exactly within this range, it indicates that the pause point has visited scenic spot S_i. After similar frequent mining, a large number of tourist attraction visit sequences can be established, as shown in Eq. (9).

$$\varepsilon \le \frac{sum(l_{ck}^i \in vk)}{sum(ck)} \tag{9}$$

In equation (9), ε represents the critical threshold, ck represents the clustering sequence with many pause points, vk represents the clustering sequence with many pause points visiting scenic spot S_i, and l_{ck}^i represents the clustering pause point with time i. In summary, the personalized recommendation model combining user spatiotemporal trajectory data is shown in Fig. 3.

As shown in Fig. 3, the model structure can be roughly divided into five parts. The first part is the target users, who have unique ideas about tourist attractions and path planning and prefer intelligent recommendations. Secondly, through spatiotemporal trajectory analysis, the second part can be obtained, which is the user pause data sequence, which records the user's spatiotemporal historical browsing data. After analyzing these pause point data through clustering algorithms, the third part, namely the user access matrix, was obtained. Meanwhile, it establishes visit sequences for frequently followed attractions, and finally personalized recommendations are made by matching the similarity between the two.

B. Construction of Travel Route Planning Model Combining Personalized Recommendation Algorithm and Improved Genetic Algorithm

In practical life, to improve the functionality of personalized recommendation algorithms, this study not only needs to construct a recommendation model for scenic spots, but also needs to substantially propose route planning methods for these scenic spots [18]. To avoid user resistance caused by the large number of personalized recommended attractions and the scattered distribution of attractions, the study introduced the Minimum Spanning Tree (MST) clustering method to prioritize the segmentation of attractions. The schematic diagram of MST is shown in Fig. 4.

Fig. 4 shows that after MST segmentation, the distance between recommended tourist attractions within the established range is significantly reduced, enabling users to visit multiple tourist attractions within a specific time range, improving the quality of travel and saving time. In addition, unlike recommending tourist attractions, the problem of recommending tourist routes is complex and variable, that is, there are multiple possibilities for planning a route to a certain location [19]. Therefore, the study introduced an improved genetic algorithm (GA) on the ground of personalized recommendation algorithms. The traditional GA is shown in Fig. 1.

Fig. 5 shows that the traditional GA in tourism route planning can be roughly divided into nine steps, including recommending a set of tourist attractions, encoding recommended attractions, determining the population, calculating individual fitness, cross mutation, selecting the best individual, updating the population, condition judgment, and outputting the best route. Traditional GAs tend to construct initial populations randomly. If a smaller initial population appears, it will affect the convergence of subsequent algorithms, leading to lower individual fitness. Therefore, the study introduced the Greedy Algorithm to improve the initialization process of the population. The improved initialization population calculation formula is shown in Eq. (10).

$$t_i = random(T), T - S \ne \varnothing \tag{10}$$

In Eq. (10), t_i represents a randomly selected attraction, T represents a set of all attractions, and S represents the initial population. At this point, the selection of nearby attractions is shown in Eq. (11).

$$\begin{cases} returnS = S.insert(t_j) \\ t_j = \min\_dis\tan ce(T - S, t_i) \end{cases} \tag{11}$$

In Eq. (11), t_j represents other attractions that are closer to the first attraction, and $S.insert(t_j)$ represents all the best individual attractions. At this point, to stabilize the individual's fitness value, the study introduced a fitness function with multiple constraints. This function includes two parts: the shortest route and the optimal access time. The fitness function calculation for the shortest route problem is shown in Eq. (12).

$$f_1(C) = \sum_{i=1}^{n`-1} d(c_i, c_{i+1}) + d(c_{n`}, c_1) \tag{12}$$

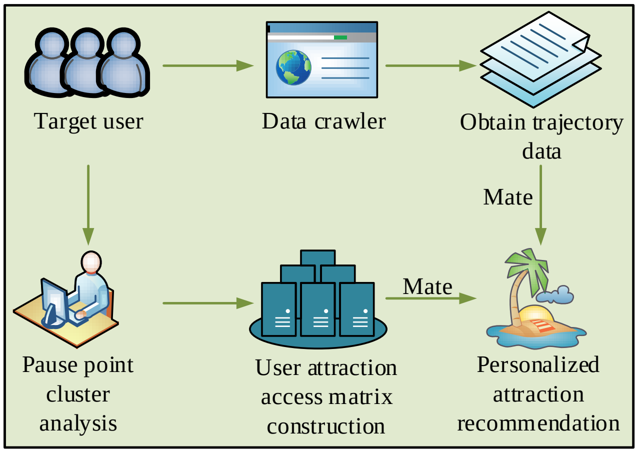

Target user
Data crawler
Obtain trajectory data
Mate
Pause point cluster analysis
User attraction access matrix construction
Mate
Personalized attraction recommendation

Fig. 3. Personalized recommendation model structure diagram.

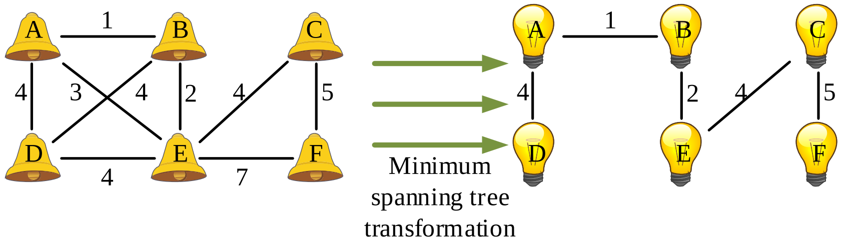


Fig. 4. MST schematic diagram.

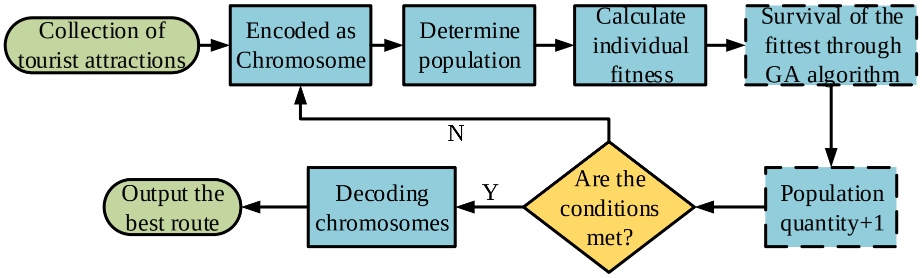


Fig. 5. The process of traditional GA.

In Eq. (12), C represents the collection of scenic spots, $n`$ represents the number of paths that satisfy user preferences, and $d(c_i, c_{i+1})$ represents the sum of distances between c_i and c_{i+1} paths. The optimal visit time needs to be planned in conjunction with the designated opening hours of the scenic spots. Due to the different opening hours of each scenic spot, the study divided the optimal visit time into three different visit times as dividing points [20]. The expression is shown in Eq. (13).

$$R(ci,t)=\begin{cases}\dfrac{2t-2t_{io}}{t_{ic}-t_{io}}, t_{io}\le t\le \dfrac{t_{io}+t_{ic}}{2}\\ \dfrac{2t_{ic}-2t}{t_{ic}-t_{io}}, \dfrac{t_{io}+t_{ic}}{2}\le t\le t_{ic}\\ 0, t<t_{io}\ \&\ t>t_{ic}\end{cases} \tag{13}$$

In Eq. (13), t_{io} represents the opening time of the attraction, t_{ic} represents the closing time of the attraction, c_i represents the attraction, and the user's visit time is t_i. Although the user's stay time at each attraction cannot be estimated, the visit time can be calculated on the ground of the popularity of the attraction. The calculation formula for conversion estimation is shown in Eq. (14).

$$t_{is}=T_N+\frac{count(c_i)}{\max(count(c_1),count(c_2),\cdots count(c_n))} \tag{14}$$

In equation (14), $count(c_i)$ represents the number of popular searches for attraction c_i, and T_N represents the time constant. By using this formula, the visit time and stay time of each attraction in a set of attractions C can be calculated. The optimal fitness function of the GA at this time is shown in Eq. (15).

$$\begin{cases}f_2(C)=\dfrac{1}{n}\sum_{i=1}^{n}R(c_i,t)\\ f(C)=\alpha f_1(C)+\beta f_2(C)\end{cases} \tag{15}$$

In Eq. (15), α and β represent the limiting weights of the fitness function for the shortest route and optimal access time, respectively. The best individual selected, crossed, mutated, and determined through GA is the optimal travel planning route for user needs. In summary, a new intelligent travel route recommendation model has been proposed by combining personalized recommendation algorithms and improved GAs. The structure of the model is shown in Fig. 6.

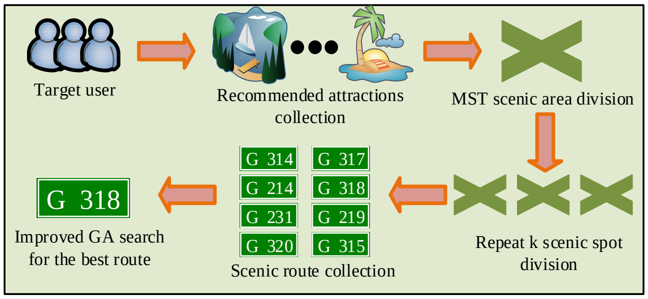


Fig. 6. Smart travel route recommendation model structure diagram

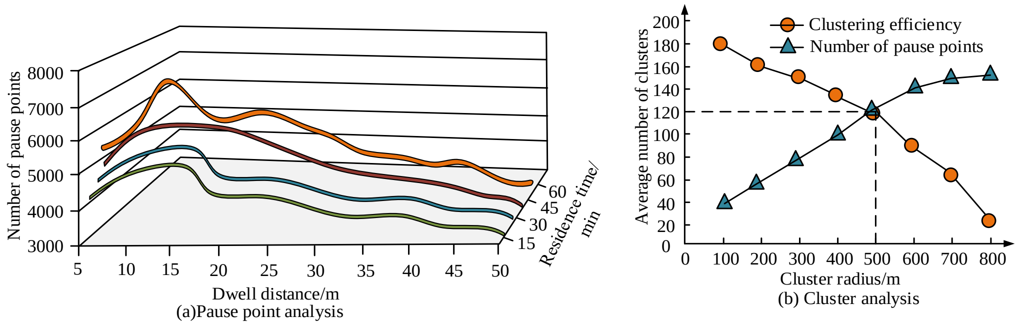
Fig. 6 shows that the entire smart travel route planning model consists of six parts. Firstly, it obtains the trajectory data information of the target user and their preferences. Secondly, it filters the target node set that best meets the user's needs through a personalized recommendation model. Then, the MST algorithm is used to divide the collection of scenic spots into regions, to reduce the recommended target. After k repeated reductions, multiple path planning schemes were finally obtained to determine the distance between scenic spots. Finally, an improved GA algorithm was used to select the optimal path set and output the best route.

IV. Results

To verify the performance of the proposed new intelligent personalized recommendation model, this study first tested the scenic spot recommendation model and determined the optimal operating parameters of the algorithm. Then it was compared with similar recommendation algorithms. In addition, the new tourism route recommendation model was tested to determine its optimal iteration times and fitness function values. It was also compared with similar recommendation models.

A. *Test Results of Scenic Spot Recommendation Model*

To verify the performance of the personalized scenic spot recommendation model proposed in the study, which combines trajectory data mining, the Windows 10 operating system was used, with an Intel Core 2.5Hz dual core CPU and 16GB of memory. To ensure the authenticity of the test, this study used a global dataset of tourist attractions and routes. This dataset contains information on various tourist attractions and related routes from around the world, totaling approximately 100000 pieces. It divides the dataset into training and testing sets in an 8:2 ratio, and the training set sample data is used to train personalized recommendation models. The study introduced two variables, dwell time and dwell distance, to analyze the pause points of users. Meanwhile, to prevent model training caused by too large or too small variables, the study sets the dwell time to within 1 hour and the dwell distance to within 50 meters. In addition, the Mean Shift clustering radius is used as a variable to detect changes in the number of clusters. The specific test results are shown in Fig. 7.



(a)Pause point analysis

(b) Cluster analysis

Fig. 7. Pause point analysis and cluster analysis parameter testing.

Fig. 7(a) shows the changes in the pause time and pause distance parameters of the pause point, and Fig. 7(b) shows the changes in the clustering radius parameters of the clustering analysis. As shown in Fig. 7, the pause change curve is most stable when the pause time is 45 minutes, and the maximum number of pauses at this time is 6000 when the pause distance is 18 meters. In addition, as the clustering radius increases, the average number of clusters gradually decreases, while the number of pause points gradually increases. When the clustering radius is 500m, that is, at the intersection, the number of the two performs best. Therefore, in subsequent research, the set parameters include a pause time of 45 minutes, a pause distance of 15 meters, and a clustering radius of 500 meters. To verify the performance difference between the personalized recommendation model proposed in the study and existing models of the same type, Tok-k accuracy was used as a reference indicator. This indicator represents the proportion of the top k results with the highest probability in the prediction results that contain correct labels, for example, Tok-5 is a test environment with 5 recommended sets. Meanwhile, the content attribute personalized recommendation model (Item based), rating personalized recommendation model (Mark based), and image personalized recommendation model (Graphics based) were introduced. The test results are shown in Fig. 8.

Fig. 8 shows that the personalized recommendation method proposed in the study generally has high accuracy in three testing environments. The highest accuracy rate in Tok-5 is 88% for the study of the proposed model, 90% for the study of the proposed model in Tok-10, and 84% for the study of the proposed model in Tok-15. In Tok-10, the accuracy of the proposed model is 33% higher than that of the content attribute personalized recommendation model and 31% higher than that of the rating personalized recommendation model. In summary, it can be concluded that the personalized scenic spot recommendation model proposed in the study, which combines temporal and spatial data trajectory mining, has the best performance. In addition, with accuracy, recall, F1 value, and recommendation similarity as reference indicators, comparative tests were continued on the four models, and the test results are shown in Table I.

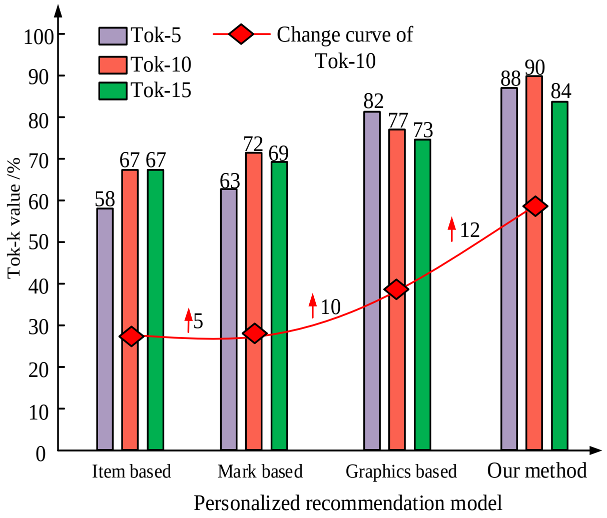


Fig. 8. Comparison results of Tok-k accuracy of different recommendation models.

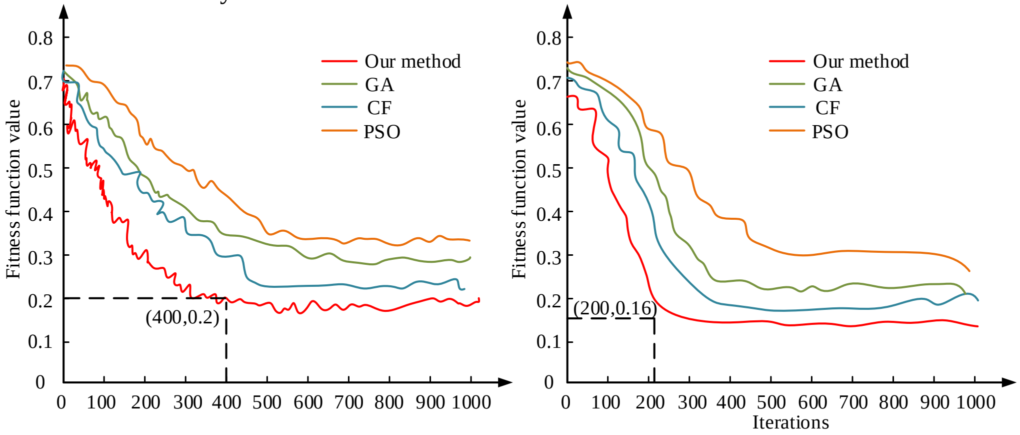
TABLE I. COMPARATIVE TEST RESULTS OF PERSONALIZED RECOMMENDATION MODELS

Model	Precision/%	Recall/%	F1/%	Recommended similarity/%
Item based	64.8	65.3	67.1	68.5
Mark based	68.4	71.6	74.8	77.9
Graphics based	74.2	75.3	76.7	79.5
Our method	82.4	84.6	85.9	89.3

As can be seen from Table I, the Item based model has generally low indicators in various categories, with its highest P value of 64.8%, highest R value of 65.3%, highest F1 value of 67.1%, and highest recommendation similarity of 68.5%. In contrast, the study proposes that the recommendation model performs the best, with the highest accuracy of 82.4%, the highest recall of 84.6%, the highest F1 value of 85.9%, and the highest recommendation similarity of 89.3%. The values rose 17.6%, 19.3%, 18.8% and 20.8% respectively compared to the lowest Item based model. In summary, it once again proves that the model proposed in the study is more in line with user choices, with higher recommendation and usage rates.

B. Test Results of Route Recommendation Model

Due to the introduction of an improved GA on the ground of personalized recommendation algorithms, this study first tested the iterative performance of the improved GA. It determines the optimal number of iterations and fitness function values to facilitate subsequent model testing. In addition, to enhance the reliability of testing, traditional GAs, CF, and Particle Swarm Optimization (PSO) were introduced in the study. These algorithms were tested separately on the training and testing sets, and the test results are shown in Fig. 9.



(a)Training set

(b)Test set

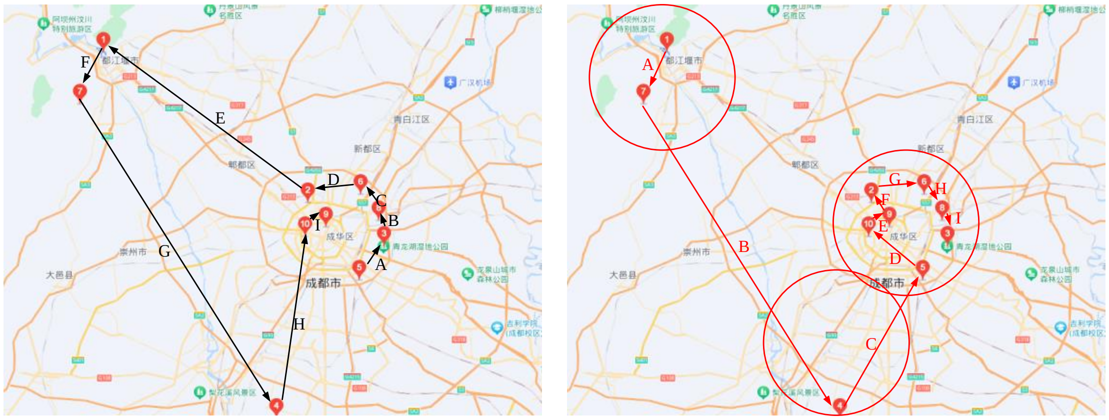
Fig. 9. Iterative performance testing of different optimization algorithms.

Fig. 9(a) shows the iterative performance test results of four optimization algorithms in the training set. Fig. 9(b) shows the iterative performance test results of four optimization algorithms in the test set. Fig. 9 shows that as the number of iterations increases, the fitness function values of all four algorithms decrease, but then tend to stabilize. The results of the training set show that the lowest fitness function value of the proposed model is 0.2 when the number of iterations is 400. In the test set, when the number of iterations is 200, the fitness function value at this point is as low as 0.16. Therefore, it is necessary for subsequent research to use the number of iterations and fitness function values as benchmarks for performance testing of similar algorithms. It conducts 50 repeated experiments on four algorithms and takes the average of the ratio of the optimal solutions obtained each time as the average convergence degree of the algorithm. Meanwhile, it continues to introduce three reference indicators: accuracy, recall, and F1 value. The test results are shown in Table II.

As can be seen in Table II, the GA algorithm has the worst performance in the metrics test, with the highest accuracy of 54.2%, the highest recall of 57.6%, the highest F1 value of 64.5%, and an average convergence of 58.8%. This is followed by PSO algorithm and CF algorithm, while the personalized recommendation algorithm proposed in the study has the highest accuracy of 85.6%, the highest recall of 88.7%, the highest F1 value of 92.4%, and the average convergence of 88.9%. To more accurately reflect the performance of the personalized tourism route recommendation model proposed in the study, the top 10 popular tourist attractions in Chengdu were selected as the target locations. They are 1) Dujiangyan Irrigation Project Water Conservancy Project, 2) Chengdu Happy Valley, 3) Qinglong Lake Park, 4) Huanglongxi Ancient Town, 5) Sansheng Flower Town Scenic Spot, 6) Giant Panda Base, 7) Qingcheng Mountain, 8) Eastern Suburb Memory, 9) Wenshu Academy and 10) Du Fu Thatched Cottage. The actual results of comparing the traditional personalized recommendation route and the new personalized recommendation route are shown in Fig. 10.

TABLE II. PERFORMANCE TEST RESULTS OF DIFFERENT OPTIMIZATION ALGORITHMS

Model	Precision/%	Recall/%	F1/%	Mean Convergence %
GA	54.2	57.6	64.5	58.8
PSO	68.4	73.2	79.5	73.7
CF	74.2	77.7	83.8	78.6
Our method	85.6	88.7	92.4	88.9



(a)Traditional personalized recommendation routes

(b)New personalized recommendation route

Fig. 10. Comparison results of personalized recommended routes.

Fig. 10(a) shows the traditional personalized recommendation route, and Fig. 10(b) shows the new personalized recommendation route. As shown in Fig. 10, the traditional personalized recommendation route connects 10 scenic spots in pairs, resulting in a total of nine moving paths, represented by black arrows. The red arrow represents the new recommended path, while the red circle tends to indicate the clustering range of scenic spots. Considering the actual situation, the maximum daily travel itinerary for users is three scenic spots. Therefore, under traditional methods, the longest crossing path for the same day's itinerary takes more time and is not conducive to users choosing fixed accommodation. The new personalized recommendation path can select at least one and at most seven stopping points within the established stopping range, and set accommodation at the center of each circle for the most convenient. In summary, the new personalized tourism path recommendation model proposed in the study performs better.

V. Conclusion

Traditional travel planning methods are usually static, only considering the user's departure and destination, without considering the user's actual behavior and real-time location. In view of this, the study established a personalized recommendation model through mean shift clustering and trajectory analysis after decomposing user trajectory data in time and space. After introducing an improved GA, a new intelligent personalized tourism route recommendation model was proposed. The experimental results show that when the pause time is 45 minutes, the pause distance is 15 meters, and the clustering radius is 500 meters, the performance of the personalized scenic spot recommendation model is the best. Compared to personalized recommendation models of the same type, the proposed model has the highest accuracy in the Tok-10 testing environment, with a maximum value of 90%. The highest model accuracy is 82.4%, the highest recall is 84.6%, the highest F1 value is 85.9%, and the highest recommended similarity is 89.3%. In addition, testing the personalized travel recommendation route model found that compared to other models, the new route recommendation model proposed in this study has the lowest iteration number of 200 and a fitness function value of 0.16. The highest accuracy of model recommendation is 85.6%, the highest recall is 88.7%, the highest F1 value is 92.4%, and the average convergence is 88.9%. Simulation tests have shown that the new model can plan more reasonable and suitable routes for the public's actual tourism, save time on route expenses, and facilitate accommodation arrangements. In summary, the new personalized attraction and route recommendation model proposed in the study can improve the effectiveness and experience of travel planning and meet user needs. However, this study only analyzed user trajectories from time and space sequences. Further research can add more user characteristic information analysis, such as subjective requirements and preferences, to enhance the completeness of the study.

VI. Discussion

The study successfully constructed a novel attraction recommendation model and travel route recommendation model by introducing improved genetic algorithm and minimum spanning tree algorithm. These two personalized recommendation models perform well in several performance metrics, highlighting their potential in the field of intelligent travel route planning. First, the optimal stopping time of the personalized attraction recommendation model is set to 45 minutes, the stopping distance is 15 meters, and the clustering radius is 500 meters when these parameters are optimized to ensure that the model can accurately capture the actual user behaviors and deviations. In particular, the model achieves 90% accuracy in the Tok-10 test environment, which is much higher than traditional personalized recommendation models, such as content attribute personalized recommendation model, rating personalized recommendation model, and image personalized recommendation model. This result emphasizes the importance of spatio-temporal trajectory data analysis in improving recommendation accuracy, and also demonstrates that the performance of recommender systems can be significantly improved by fine-grained user behavior analysis. In addition, the personalized travel route recommendation model has the highest accuracy of 85.6%, recall of 88.7%, F1 value of 92.4%, and average convergence of 88.9%. These metrics not only reflect the model's efficiency and accuracy in the field of travel route recommendation, but also show the effectiveness of the improved genetic algorithm in dealing with complex route planning problems. By introducing the greedy algorithm to optimize the initial population and adopting the fitness function with multiple constraints, the study successfully improves the convergence speed of the algorithm and the quality of recommendations. However, there are still some potential challenges and limitations of these models. First, although the studies have achieved significant results in specific datasets and environments, their generalization capabilities still need to be validated in a wider range of scenarios and complex user behavior patterns. In addition, the performance of the model relies heavily on high-quality spatio-temporal trajectory data, and thus, it may face challenges of privacy protection and data security in data collection and processing. In response to the above discussion, future research could further explore the application of the model in different cultural and geographic contexts to validate its generalization ability. Second, considering the importance of data privacy and security, future work should focus more on the anonymization of user data and the application of encryption techniques. Finally, given the diversity and dynamics of user preferences, the development of more flexible and adaptive models will be the key to improving the accuracy and user satisfaction of recommender systems.

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Animation Media Art Teaching Design Based on Big Data Fusion Technology

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***Abstract*—Animation, as an ancient art expression form, still has vigorous development, and the need for animation talents in society is increasing daily. This study first introduces the definition of animation and the development of animation at home and abroad. After that, the classification regression tree algorithm's principle and function theorem are described. This study divides the data into original and new animations based on big data fusion technology. It establishes a media art teaching system with search, recommendation, and playback as the three cores. Additionally, iteration is used to calculate the optimal hidden semantic matrix, a comparison is made between the benefits and drawbacks of the Sigmoid, Tanh, and ReLU functions, and lastly, the activation function chosen is the ReLU function. Compared with the loss value in the ideal case, the experimental findings comply with the likely criteria, and the categorical regression tree algorithm model predicts an error rate that falls within acceptable limits. Practically speaking, it is known that when the hidden factor dimension is 12, the system model works best for characterizing animation features. The comparison shows that the non-standard collaborative filtering recommendation system is inferior to the recommendations filtered by the categorical regression tree algorithm model. Following the use of the system, the students' drawing and directing abilities, animation scope, and animation appreciation level all improved significantly. The questionnaire survey concluded that the teachers and students of animation majors in universities were satisfied with the system.**

Keywords*—Animation; big data fusion; classification regression tree algorithm; media art teaching system

I. Introduction

The rapid development of computer technology has generated massive amounts of data, and studying these data has, in turn, driven the development of computer technology. It is the era of big data, and along with the widespread appeal of computer mainframes and mobile phones, the amount of people using the Internet has increased dramatically. The Internet has grown quickly as a result of technological developments as well, and humans today have access to hundreds or even thousands of times more data every day than they did in ancient and modern times [1]. According to an International Data Institute report, the global data volume is anticipated to reach 56 ZB by 2030 [2]. Animation from the generation and dissemination also took advantage of the development of the Internet. They grew up, and the larger bandwidth and more rapid transmission speed both provide a broad and excellent soil for the production and dissemination of animation.

The abundance of information brings about convenience and the issue of information overload, which presents a significant obstacle for information producers and consumers. For information producers, the material they create can easily be submerged in the data of the Internet and cannot distinguish themselves from others. Much information is available to users, and separating the helpful information is challenging, wasting time and energy [3]. Universities and art colleges are particularly affected by this issue, where educators have access to abundant information resources and must exert significant effort to select only those appropriate for their teaching. Students still lack a solid worldview, life perspective, and set of values, and separating the good from the bad is challenging when they receive mixed information [4]. The search, recommendation, and viewing system for teaching animation media art based on big data fusion technology came into being, providing some convenience to users; however, users' needs are different; exceptionally productive students have specific needs for searching, recommending, and viewing animation media data [5]. Throughout human history, animation has evolved to communicate ideas and express feelings. From the eight-legged bison drawn in caves by ancient humans with black charcoal in the late Paleolithic to the continuous wrestling figure on ancient Egyptian frescoes, from the first animated film "Enchanted Pictures" to Disney's first 3D animated film "Toy Story," animation development has now become a spiritual totem for some people [6]– [9]. As the era of Big Data storage began to emerge, revolutionary changes have also occurred in the distribution media. From videotape to CD-ROM until nowadays, online streaming media and animation present accessibility, convenience, and technological development [10]. For art college and university students, especially those majoring in animation-related disciplines, searching, recommending, and viewing animation media data are critical to developing skills and knowledge.

Currently, in daily life, search engines are used extensively to offer consumers both basic and extensive search services in addition to conventional search engines. The integrated search engines of music, video streaming, social media, and knowledge quiz software are also receiving increasing attention, and this software faces a great challenge in delivering more accurate, timely, and convenient search results. The animation art teaching system assisted by big data fusion technology is the search function is the foundation, and only when the animation data is well searched can educators and learners gain from it [11]. Suggestion systems, on the other hand, have evolved from streaming services and are now most frequently applied in e-commerce applications for product recommendations. In the animation market application, incorporating a suggestion system enhances the positive user experience while increasing active product users. User stickiness rises as a result, making users see more different styles of animation works and eventually greatly improving commercial interests [12]. Viewing animation is as important for art students in animation as it is for college students in other majors to read material related to their major, sometimes even watching and analyzing an animation frame by frame, and this way of learning is called pulling a film [13]. In the teaching system of art colleges and universities, with the ongoing advancement and use of computer convergence technology, the animation industry has favored the provision of online streaming media, where teachers and students can easily access resources in a variety of ways, such as online viewing and downloading using video websites and cell phone applications. However, animation databases are becoming larger and larger, and college art students have to spend a lot of time and effort to find the right animation for them. In the past, Users were limited to searching using keywords such as name, director, and style of animation, and the variations among users were not considered in the search results, leading to biased results [14].

The growing volume of animation data and demand from students and faculty in universities and art colleges demonstrates a more difficult task for studying animation search, recommendation, and viewing algorithms. Conventional recommendation systems fall into three main categories: content-based recommendations, collaborative filtering, and hybrid recommendations combining the two. Even so, these three categories of fundamental suggestion methods have been advanced; they have serious issues, like sluggish startup times [15]–[17]. In addition, the recommendation based on sentiment status, which developed along with social media, has also come into view with the public, resulting from the computer industry's deep learning and thorough exploration of the possible interests of users. This paper, based on classification regression tree theory, starts by analyzing the characteristic data of art school teachers and students and their animation preferences to design a motion search system with accuracy, personalized music recommendation, and a virtual reality viewing system, which is the goal of every art college and which can also greatly facilitate teaching and learning for teachers and students daily. Thus, it has significant research implications and a wide range of potential applications.

1) This study innovatively applies the classification regression tree algorithm to preprocess animation data and train models. By replacing the predicted feature coefficients, effective data preprocessing of the animation video library was achieved, improving the prediction accuracy and stability of the model.

2) The research system fully utilizes the advantages of big data to achieve precise satisfaction of personalized needs of students, improving teaching effectiveness and student satisfaction. The construction of this system provides a new teaching mode and method for animation media art teaching.

3) This study compared the advantages and disadvantages of Sigmoid, Tanh, and ReLU functions, and ultimately chose ReLU function as the activation function. This choice effectively improves the training speed and performance of the model, providing strong support for the optimization of animation media art teaching models.

This study establishes a media art teaching system based on big data fusion technology, with search, recommendation, and playback as the three core elements. Section II of the study elaborates on the background of animation media art teaching based on big data fusion technology. Section III elaborates on the analysis of animation and animation applications. Animation has evolved from two-dimensional to three-dimensional, expanding its application scope. The principle and selection analysis of the classification regression tree algorithm were conducted in Section IV. The implicit feature analysis of iterative animation was conducted through a mixed model of user behavior and animation media data information. Section V conducted teaching system practice and effectiveness analysis. It uses the predicted feature coefficients of the input classification regression tree algorithm to preprocess the data of the animation video library. Through animation teaching classroom tests, the abilities of college students in related majors were tested. It shows that animation students have improved their drawing and directing skills, their animation scope, and their appreciation of animation through this system. Section VI summarizes the entire text. Students majoring in animation production have significantly improved their drawing and directing skills, animation scope, and animation appreciation level by using this system.

II. Related Work

Previous research has provided us with the development history of animation media art, from early hand drawn animation to modern digital production technology. These studies help us understand the evolution of anime art and how it combines with technological advancements. Previous research has contributed to the theoretical framework of animation art instructional design. They explore different teaching methods, strategies, and evaluation methods, providing us with a solid theoretical foundation to better design and implement animation media art teaching. With the rapid development of technologies such as big data and artificial intelligence, previous research has explored the application of these technologies in other fields. These studies provide us with valuable experience, enabling us to draw on and apply them to the design of animation media art teaching.

The teaching design of animation media art based on big data fusion technology is expected to bring revolutionary changes to animation education. Through the analysis and mining of big data, we can more accurately understand the learning needs and effects of students, and thus design more personalized and efficient teaching methods. Through real-time data analysis and feedback, we can adjust teaching strategies in a timely manner to ensure optimal teaching outcomes. This will help cultivate students' creative thinking and practical abilities, and provide more high-quality talents for the animation industry. Animation is the art of "tricking" the eye, based on the same principle as film. It is a film technique that uses the visual residuals of the human eye to create the illusion of movement of objects within the image by showing still images at a fixed frequency [18]. From its inception, animation has been an art form, combining many characteristics of painting and film. Because the location and environment do not limit it, it expresses a wild imagination.

It has broadened its application after the development of animation from a two-dimensional to a three-dimensional stage. In contemporary times, animation is mainly used in entertainment, with animated episodes, movies, special effects, games, and animated advertisements being its main battleground [19]. The field of animated episodes has been gaining momentum in recent years, making hundreds of millions of people feel the charm of animation by disseminating online streaming applications such as Netflix, Disney, and HBO. Among them, "Love, Death and Robots" has created high ratings and topics with its mature animation technology, deep thought expression, and amazing picture expression, the masterpiece of American animation in the new century [20]. Digital fusion technology, including virtual reality, augmented reality, mixed reality, etc., has brought unprecedented possibilities to visual art design. These technologies not only enable designers to present artworks in unprecedented ways, but also allow audiences to immerse themselves in them and gain a more profound artistic experience. Therefore, studying the impact of digital fusion technology on visual art design is of great significance for promoting the development of the art and design field [21]. The basic principle of digital fusion technology is to combine digital information with the physical world to create a brand new and immersive experience. For example, virtual reality technology simulates a three-dimensional environment, allowing users to experience the virtual world firsthand; Augmented reality technology adds digital elements to the real world, allowing users to observe the world from a completely new perspective [22]. These technologies provide a new creative medium for visual art design, enabling designers to present artworks in unprecedented ways. The emergence of digital fusion technology has brought about a profound transformation in the form of visual art design. Firstly, designers can utilize these technologies to create more realistic and immersive works of art. Secondly, digital fusion technology allows artworks to no longer be limited to traditional media such as painting and sculpture, but can be extended to various media such as virtual space and mobile devices. In addition, digital fusion technology also provides designers with richer creative tools, such as 3D modeling software, virtual reality editors, etc., allowing them to create art works in unprecedented ways [23].

In contrast, China's animation has been in a disadvantaged position in the world since the peak of "The Greatest Showman" at the beginning of the country's founding. The animation industry is far below Japan and the United States in terms of both artistic value and commercial output. Creating animation with its national characteristics, artistic expression, and commercial value has become the challenge and goal of every animation producer in China. This study aims to use big data fusion technology to create an animation teaching system suitable for university teachers and students and make some contribution to the animation education industry. Fig. 1 shows promotional images for the "Love, Death, Robot" series of animations.

Fig. 1. Promotional image for the animated series from Love, Death, and Robots.

III. Principle and Selection of Classification Regression Tree Algorithm

The definite regression tree algorithm is built depending on the prior distribution, the distribution set before the experiment. From there, it extracts the posterior distribution of the sample. So, the regression tree theorem, also known as the posterior probability, is the likelihood that event N will occur under the conditions after event M, which the following equation can express.

$$P(M|N) = \frac{P(M \cap N)}{P(N)} \tag{1}$$

The posterior probability is not the same as the joint or prior probability, which is the likelihood of two occurrences, M and N, occurring simultaneously. And the opposite of the posterior probability is the prior probability. The prior probability can be marginalized to give an alternative expression for the regression classification tree algorithm. That is, according to the equation that follows.

$$P(M|N) = \frac{P(M|N)P(M)}{P(N)} \tag{2}$$

Where $P(M|N)$ denotes the probability of event M occurring in the case of event N.

A. Overall Design of Animation Media Art Teaching System

The recommendation systems for text, photos, music, and videos have extensively used the categorical regression tree algorithm. This study of an animation content search, recommendation, and viewing system for art school college students is a hybrid model of recommendation based on user behavior and animation media data information. Using a classification regression tree algorithm, this search's primary objective and recommendation are to compute the implicit features of the animation media data iteratively and then obtain the data's low-dimensional vector information through marginalization. This low-dimensional vector information can be included in the search to enhance the search results. By merging them with the implicit preference features of college-going users, reasonable recommendations can also be generated. This experiment directly extracts the image and audio features from the animation video files. This can overcome the cold start problem and be as close to the user's innate sense of animation as possible. The conventional matrix-based decomposition model is the basis for this hybrid system and is enhanced algorithmically. Fig. 2 below shows the general flowchart for system design.

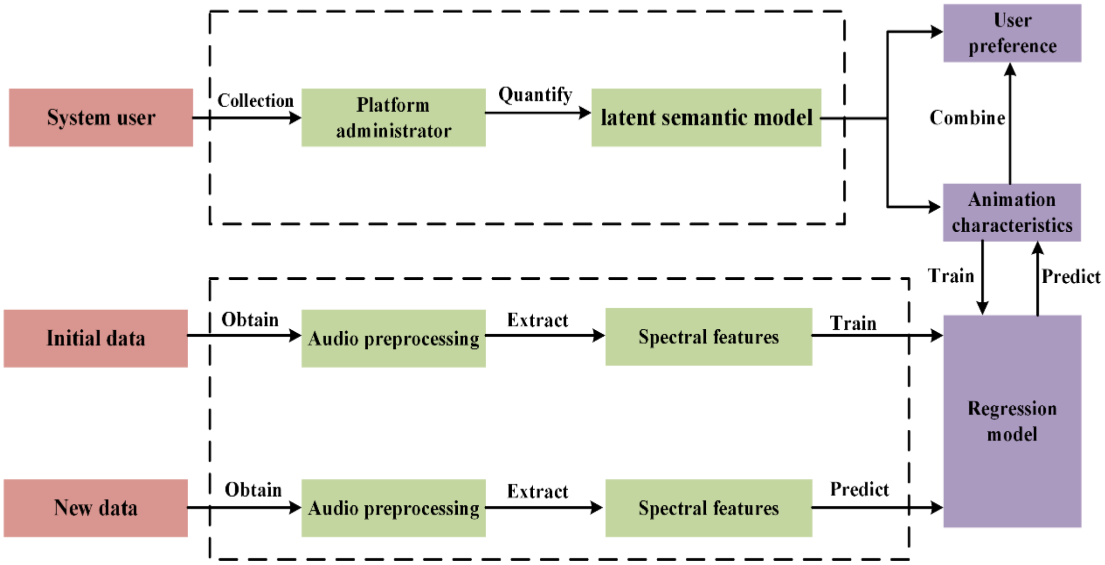

Fig. 2. Flow chart of the overall design of the animation big data management system for college students.

The above figure shows that the model utilizes a covert semantic matrix to map user-hidden traits and animation video data into a common space using a classification regression algorithm, ultimately producing search and recommendation outcomes. The animation media art teaching data system in colleges and universities includes a user features module, animation video information, a search engine module, a recommendation algorithm module, and virtual reality playback equipment. The user features module's primary responsibility is to gather and preserve student users' behavioral history data within the system and then build their preference models. Based on the extracted features, the search engine module generates customized search results for the user. Calculating the degree of matching between student users and hidden features is done through the recommendation algorithm module, and, finally, recommend animations that may be interesting for users dynamically. The two main components of the entire system operation are classification regression tree model training and search recommendation, and the processes of acquisition, prediction, and aggregation are indicated by arrows in the figure. The steps involved in the particular process are as follows: first, the system uses online streaming software to gather historical user behaviors from students and unifies them for analysis using a suitable semantic matrix; then, the raw animation data are reduced and processed to extract image and spectral features; a dynamic model of classification regression tree is constructed using the data collected in the first two stages, and then the resulting data are input and continuously. Finally, if new animation data is added to the system, the same reduction is performed to obtain the image and spectral features. Then, the perfect model is used to determine how interested a user is in the new animation data in combination with the preference of college students and, ultimately, decide whether to advise the user to use it.

The system must also categorize the original and updated animation data. Traditional animation is based on name, director, scriptwriter, Production Company, and file format classification. Certain similarities can be found in the automatic animation classification method based on style and emotion. The classification regression tree algorithm must be run through three steps to extract features, select the best features, and classify training. The two, nevertheless, are very different because the traditional animation classification's qualitative features are not the same as the abstract definitions of style and emotion in animation. The style and emotion of animation are derived from the subjective emotions of humans, which is a high-level way to describe the experience. Style is established by classifying different artists while making animation works by their starting points and common points. It can serve as a condensed synopsis of the works of specific directors. The topic of animation is expressed through emotion, has a decisive role in evoking the viewers' feelings about the work, and can be utilized as a concise overview of the shared aspects of certain animation works according to the plot and character portrayal stereotypes. More animation materials are available now than ever due to the animation business's growth. It is of great importance for the advancement of the animation industry that animation students and teachers quickly connect and enumerate the information using style and emotion classification when searching for the required materials, which determines the merits of a certain database. The animations produced by the same animation director at different times may have different ideas or styles. The subset of features obtained by the categorical regression tree algorithm can be used to form a hierarchical relationship map for the perception of animation works according to style and emotion.

B. *Constructing the Hidden Semantic Matrix*

A Basic Factorization Matrix (BFM) is the hidden semantic matrix used in the animation media art teaching system, which does not break down the scoring matrix into the form of a product of three matrices, in contrast to the traditional singular decomposition matrix. Multiple users and multiple items are broken down into a matrix of hidden factors corresponding to users and a matrix of hidden factors corresponding to items by the hidden semantic matrix. Complementing the original matrix is not necessary, and finally, the matrix is fitted using the obtained hidden factors to obtain the predicted scores. The following equation can express this process.

$$\overline{R}_{\alpha\times\beta} \approx R^2_{\alpha\times\beta} = P_{\alpha\times k} Q^T_{\beta\times k} \tag{3}$$

The variables $^{\alpha}$ andβ represent the number of student users and music, respectively, and$R^2_{\alpha\times\beta}$represent the approximate square matrix resulting from the decomposition of the two matrices, which goes by the name of the estimated rating matrix. The following formula can be used to determine an animation's expected rating by a student user.

$$p_u q_i^T = \sum_{k=1}^{K} p_{uk} q_{ki} \tag{4}$$

The hidden semantic matrix can be well used to represent the student user's preference for the underlying features of the animation using hidden factors and lessening the matrix decomposition's complexity. The next step requires computing the two hidden factor matrices$P$ and,Q initializing them, and then iterating them continuously using the stochastic gradient ascent method until a local optimum is reached. The following equation can define the error in scoring for every student user.

$$e_{ui}^2 = (r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})^2 \tag{5}$$

This study uses squared error to lessen the discrepancy between the expected and real scores by first defining the loss function as:

$$arg\,L\,oss = \sum e_{ui}^2 = \sum (r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})^2 \tag{6}$$

Then, find the direction of the current value's positive gradient, using two directional variables to differentiate.

$$\begin{cases} \frac{\partial}{\partial p_{uk}} e_{ui}^2 = -2q_{ki} = -2e_{ui}q_{ki} \\ \frac{\partial}{\partial q_{uk}} e_{ui}^2 = -2q_{ki} = -2e_{ui}q_{ki} \end{cases} \tag{7}$$

Update rules are then developed to iterate over the gradient up direction.

$$\begin{cases} p_{uk} + a\frac{\partial}{\partial p_{uk}} e_{ui}^2 = p_{uk} + 2ae_{ui}q_{ki} \\ q_{uk} + a\frac{\partial}{\partial q_{uk}} e_{ui}^2 = q_{uk} + 2ae_{ui}p_{ki} \end{cases} \tag{8}$$

The constant in the above equation a determines the machine learning rate's minimum value, which is a small value. The gradient ascent process is iterative and continuously performed until the smallest possible mistake is made. When the loss function's error is smaller, the iteration comes to an end, then the set threshold$e$ and two matrices are ultimately obtained as:

$$E = \sum e_{ui}^2 = \sum (r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})^2 \leq e \tag{9}$$

Hidden Semantic Matrix Decomposition can be done using the simplest formula above, and direct loss function optimization cannot be performed due to the ease with which overfitting may result. In this experiment, the original loss function is subjected to the regularization term, i.e., after introducing regularization, the loss function is expressed as follows:

$$e_{ui}^2 = (r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})^2 + \lambda(\|p_u\|^2 + \|q_i\|^2) \tag{10}$$

$$arg\,L\,oss = \sum \begin{matrix} (r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})^2 + \lambda(\|p_u\|^2 \\ +\|q_i\|^2) \end{matrix} \tag{11}$$

Systematic experiments can be obtained from the above equationλ, which is the regularization parameter. Eq. (11) is optimized using the stochastic gradient ascent method, where the two matrices are first biased.

$$\frac{\partial Loss}{\partial p_{uk}} = -2(r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})q_{ki} + 2\lambda p_{uk} \tag{12}$$

$$\frac{\partial Loss}{\partial q_{ki}} = -2(r_{ui} - \sum_{k=1}^{K} p_{uk} q_{ki})p_{uk} + 2\lambda q_{ki} \tag{13}$$

The parameters in the above two equationsp_{uk} andq_{ki} are then iteratively optimized along the minimum value of the velocity rise using alternating least squares to obtain the optimal parameter values.

$$\overrightarrow{p_{uk}} = p_{uk} + a(e_{ui}q_{ki} - \lambda p_{uk}) \tag{14}$$

$$\overrightarrow{q_{ki}} = q_{ki} + a(e_{ui}p_{uk} - \lambda q_{ki}) \tag{15}$$

The ideal hidden semantic matrix is thus obtained in this manner for this experiment, after which the parameter selection of the required functions is carried out.

C. Activation Function of Animation Media Art Teaching System

Without an activation function, the categorical regression tree model would only be comparable to a linear regression model and be unable to solve logical problems that were more complicated. When activation functions are introduced, a nonlinear processing model replaces the monotonic model in dynamic systems, allowing more complex animated data to be represented and computed. Today, Sigmoid, Tanh, and ReLU functions are the three monotonic functions that are most commonly utilized, and the accompanying function diagrams are displayed Fig. 3 below.

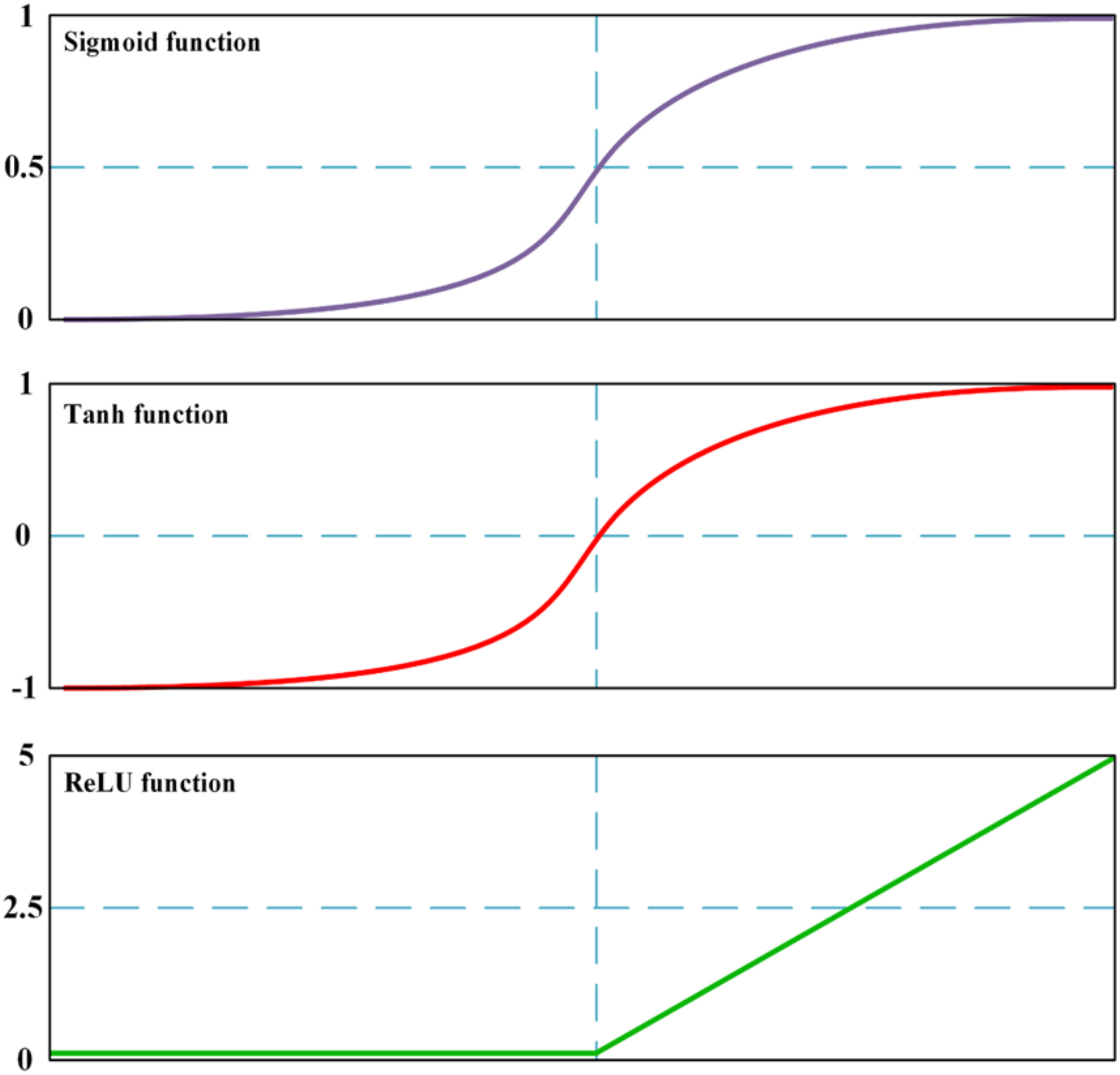

Fig. 3. Schematic diagram of Sigmoid function, Tanh function, and ReLU function.

The selection of various activation functions applied to the animation art teaching system will affect prediction and training, impacting the search and recommendation outcomes. Significant errors are produced when computing large amounts of data using the Tanh or Sigmoid functions; when utilizing the ReLU activation function, convergence can occur rapidly, reducing computation costs and increasing training effectiveness. Additionally, the ReLU function's gradient is constant for the dynamic deep animation art model, and unlike in the case of the Sigmoid function, there is no gradient disappearance. Consequently, as previously indicated, the activation function of this study's animation art teaching system is ultimately chosen to be the ReLU function.

IV. Teaching System Practice and Results Analysis

In computer deep learning, numerous open-source, free benchmark databases are available at home and abroad, but most are text, images, audio, and surveillance videos. In most cases, copyright ownership is involved in the animation data needed for this experiment, so a license was obtained with an online animation video software and applied to practical utilization of the system within an art university. First, data preprocessing is performed on an animation video library using predicted feature coefficients substituted into a classification regression tree algorithm. As previously mentioned in the section, the squared error is the loss function in this experiment. The media art teaching model is trained using the animation video data preprocessed above, and the training outcomes are displayed in the following Fig. 4.

As the resulting graph illustrates, in the early stages of training, the loss error rapidly reduces, and once the iteration round epoch surpasses 20, the function's decreasing trend is moderately delayed. Compared to the ideal case's loss value, the experimental findings align with expectations, and the classification regression tree algorithm model's prediction error falls within allowable bounds.

Then, the epoch was evaluated more comprehensively using the hidden factor dimension, and the animation video media files' number of feature vectors directly influenced the hidden factor's output dimension size. Experimentally, 248 animation students using the animation media data system were selected. When the hidden factor dimension was raised from 4 to 14, it impacted the iteration rounds, and the results are displayed in the following Fig. 5.

The greatest RMSE value can be found using the experimental findings shown in the above figure when the dimension of the hidden factor is 4, either the Epoch number is 20 or 40, which suggests that when the dimension is small, the characterization of animated images and audio features is inadequate. The RMSE value steadily drops as the dimension rises and is at its minimum when the hidden factor's dimension is 12, after which the RMSE value increases again as the dimension increases. Therefore, it can be concluded that the system model performs best for animation features when the hidden factor's dimension is 12.

The system model's accuracy and recall were tested under various recommendations and searches to verify the feasibility of this experimental categorical regression tree algorithm. The obtained results are plotted as shown below.

A comparison of the accuracy rates in the Fig. 6 shows that the accuracy rates of the recommendations using the classification regression tree algorithm model are considerably greater than those of the standard collaborative filtering recommendations after filtering the features of the animated videos and without this method. The results of the recall rate comparison between the two different algorithms are analyzed again. As the figure illustrates, the two algorithms' recall rates progressively rise as the animation search, recommendation, and viewing lists grow. An acceptable recall is attained when the recommendation list is 45, at which point the recall of the animated video data search, recommendation, and watch using the categorical regression tree model is 4.65%, while the recall of the non-standard collaborative filtering animated video data search, recommendation and watch is about 6.31%. The comparison demonstrates the influence of recommendations after filtering by the categorical regression algorithm model is superior to the irregular collaborative filtering recommendation system.

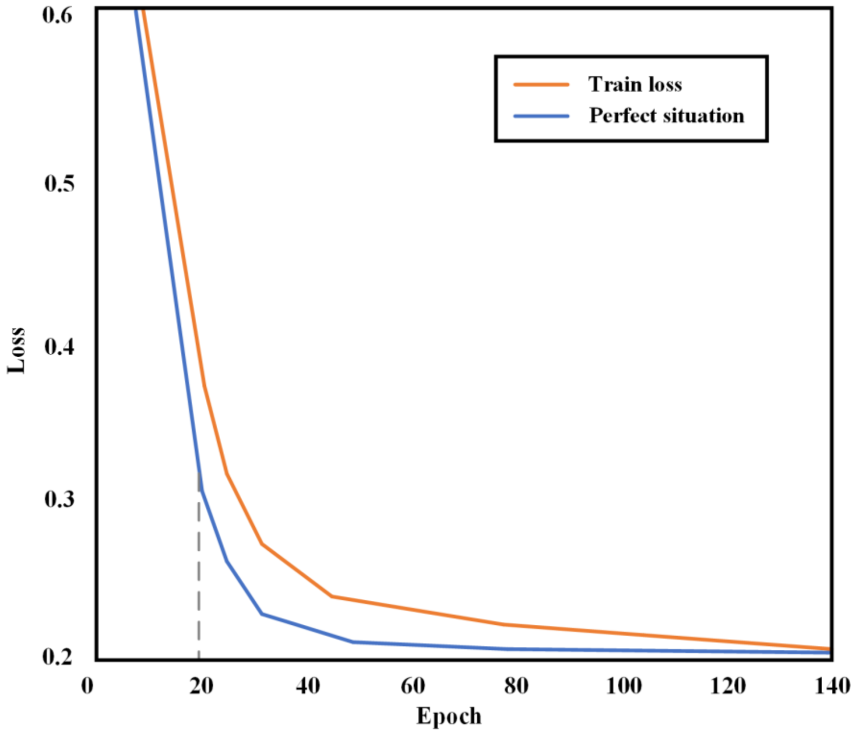

Fig. 4. The relationship between the ideal value and the loss value of the training model.

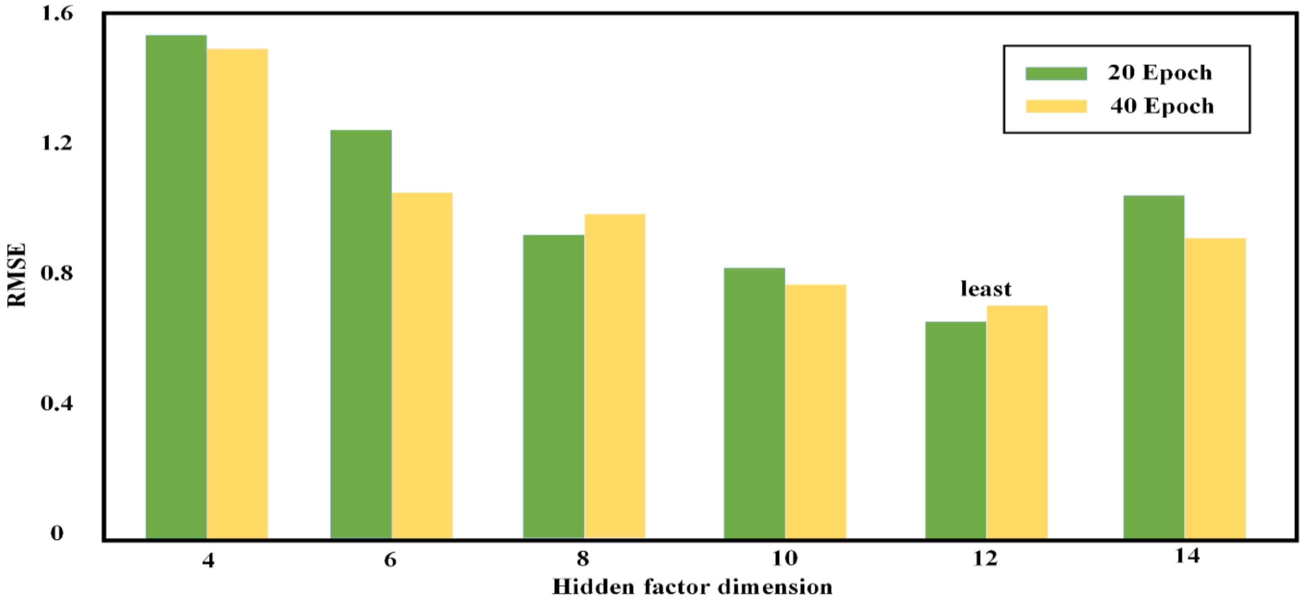

Fig. 5. RMSE of predicted scores at different k and epoch.

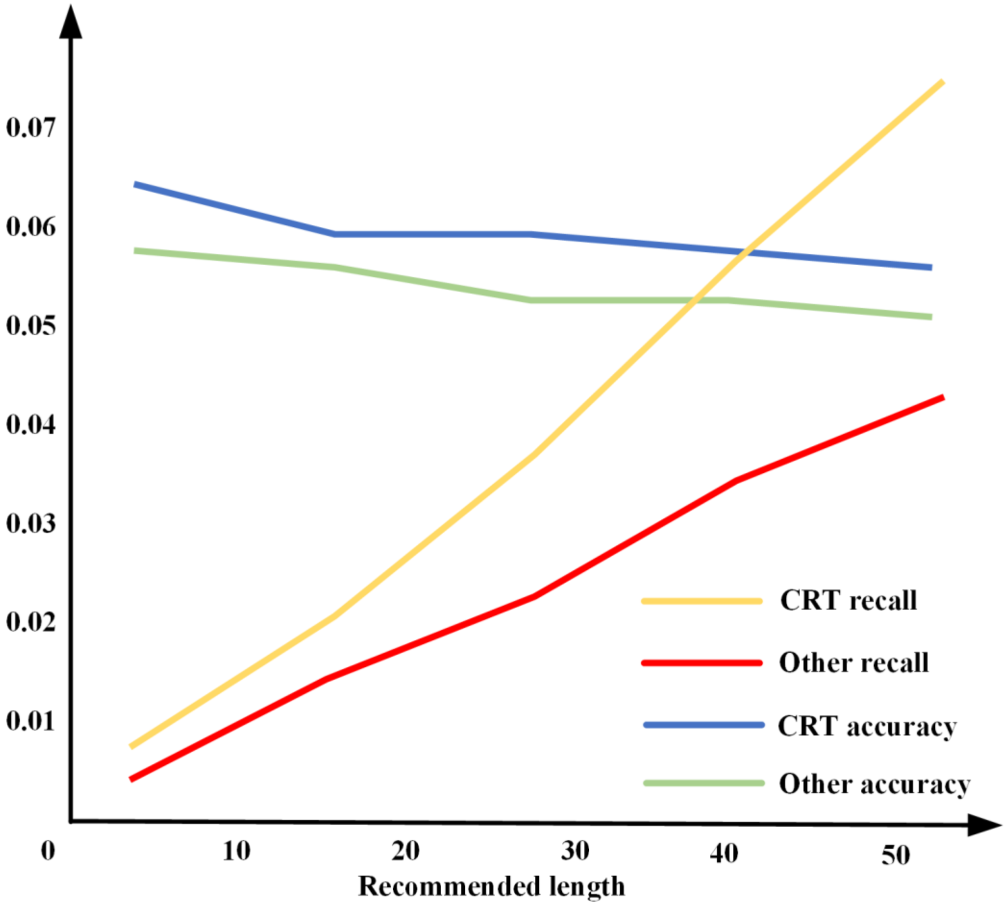

Fig. 6. Comparison plot of precision and recall for two different algorithms.

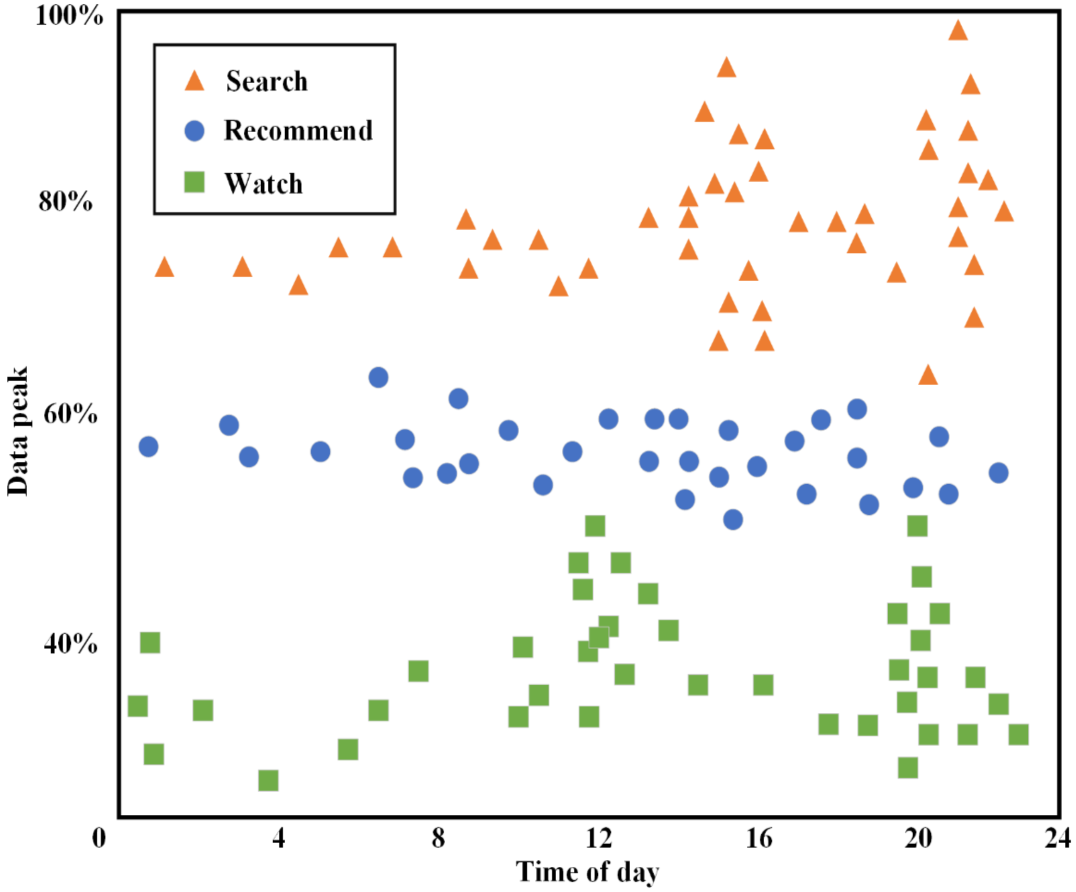

Fig. 7. Graph of peak data searched, pushed, and watched throughout the day.

The animated video data in the system has three-dimensional features. The data is dimensionally reduced to represent the database using low-dimensional data to optimize management. As shown in the Fig. 7 above, the low-dimensional data can accurately reflect the results and has no redundant features, making it faster and easier to calculate search, recommendation, and viewing results for the low-latitude data.

The above figure depicts the data peaks of the animation students searching, pushing, and watching animations during the entire day. The recommendation data peaks of the college students during the day are kept within a reasonable range without abnormal peaks and underestimations. This suggests the experiment's data system is stable and not overly resource-intensive when computing and producing recommendation results, which meets the requirements of faculty and student users. There will be two data peaks during the search, at 15:00 and 21:00. Because these two times correspond to the most frequent demands of students for entertainment and classes, this essay speculates that there might be such search peaks. The average data of the recommendation system indicates that the system makes stable recommendations at each time slot. The viewing behavior peaks at 12:00 and 20:00, which is caused by the analysis that students have the behavior habit of watching animation during lunch break and evening break time. The stability of the peak value of daytime recommendation data indicates that the system can continuously and accurately provide recommendation services to users without excessive resource occupation. The average recommendation data indicates that the system can maintain stable recommendation performance at different time periods. Through classroom testing of animation teaching, it was found that students have improved in painting, directing skills, animation scope, and animation appreciation, proving the effectiveness of the system in teaching.

After implementing the animation media art teaching system based on big data integration technology for seventy days, college students' ability in related majors was examined through animation teaching classroom tests. Fig. 8 below shows that the animation students have improved their drawing and directing skills, their scope of animation, and their appreciation of animation through the system.

The results were used for a while. The feedback from the teachers and students of the animation majors in the universities involved in the experiment was acquired using a survey. Fig. 9 below displays the results.

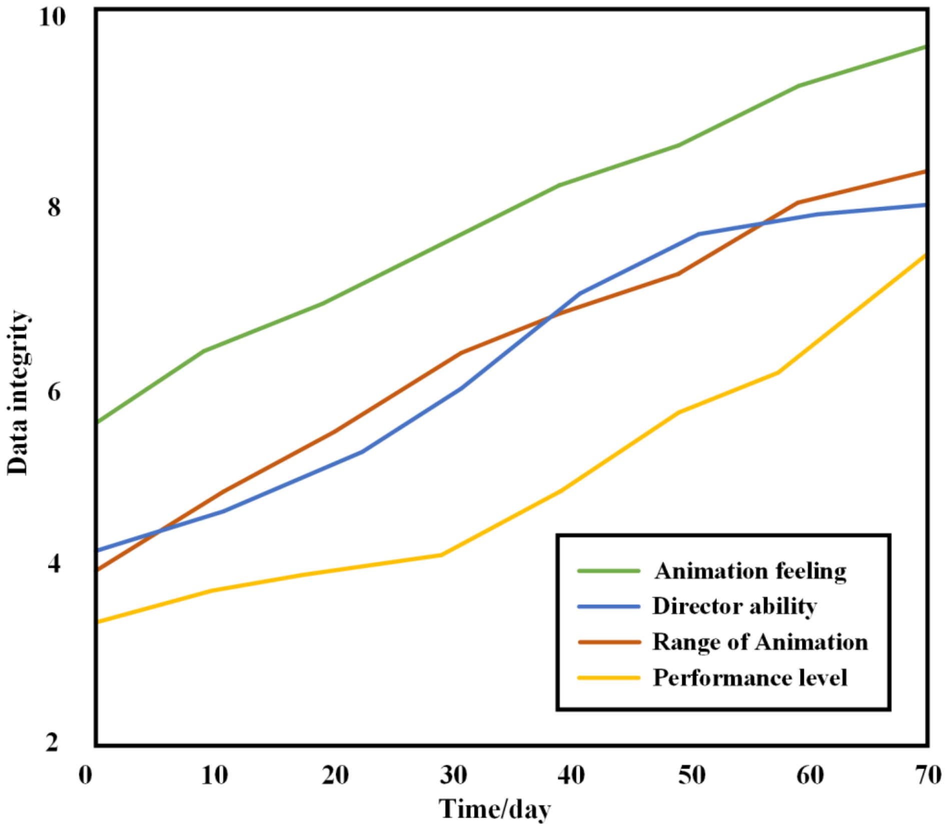

Fig. 8. The relationship between students' animation scores and days under classification regression tree model data mining.

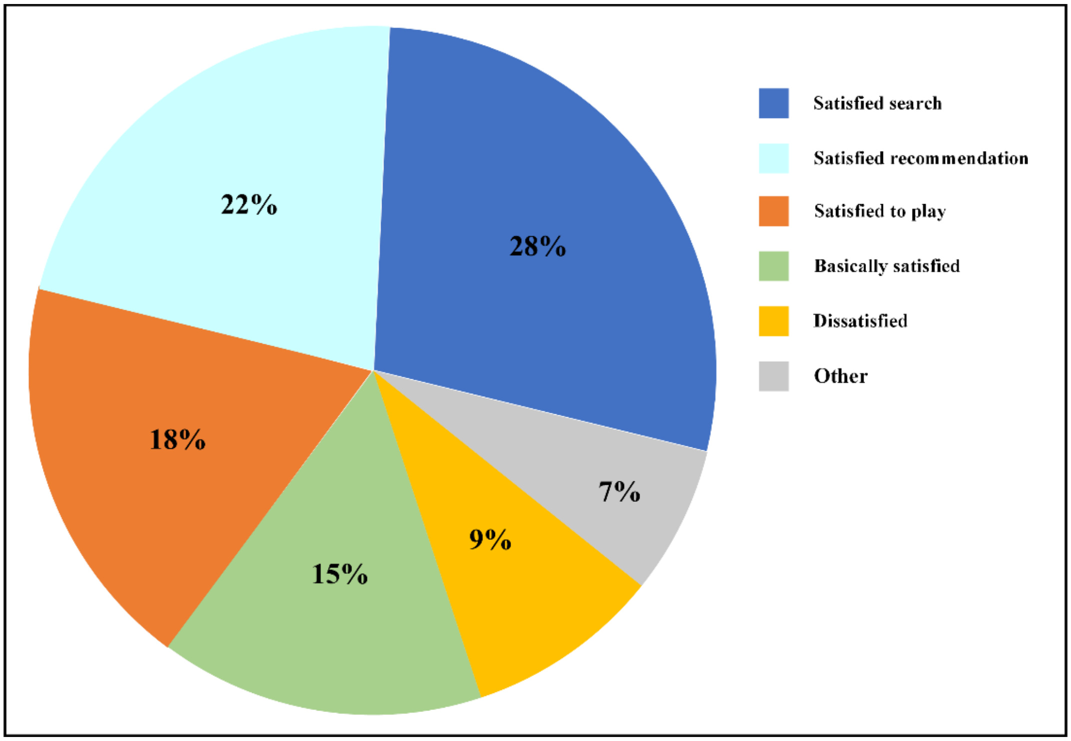

Fig. 9. The results of the teacher and student satisfaction survey of the animation media art teaching system.

V. RESULTS AND DISCUSSION

After a series of experiments and practices, the animation media art teaching system based on big data fusion technology has shown significant results. Firstly, by substituting the predicted feature coefficients of the classification regression tree algorithm into the animation video library for data preprocessing, the system can accurately extract and characterize the features of animation data, providing a high-quality dataset for subsequent teaching model training. During the training process, the loss error rapidly decreases and tends to stabilize after a certain iteration period, indicating that the model has a good fitting effect on the data and the prediction error is within an acceptable range.

When evaluating the impact of hidden factor dimensions on model performance, the experiment found that the system performed best when the hidden factor dimension was 12. At this point, the model is able to effectively extract features from animated videos and performs well in search, recommendation, and viewing. This discovery is of great significance for optimizing model structure and improving system performance.

Compared with traditional collaborative filtering recommendation systems, recommendation systems based on classification regression tree algorithms exhibit advantages in accuracy and recall. Especially in the search, recommendation, and viewing of animation video data, the classification regression tree model can more accurately filter and recommend animation content that meets user needs, improving the usability and user experience of the system.

In addition, the system optimizes data management through dimensionality reduction techniques when processing animated video data with three-dimensional features, enabling low dimensional data to accurately reflect results and improving search, recommendation, and viewing efficiency. In practical applications, the stability and performance of the system have also been verified, meeting the needs of teachers and students.

VI. CONCLUSION

This study is based on big data fusion technology and successfully constructed an animation media art teaching system, which was applied in a practical teaching environment for 70 days. By substituting the classification regression tree algorithm for data preprocessing and model training, the system demonstrated good predictive performance with errors within the allowable range. When evaluating the impact of hidden factor dimensions on model performance, it was found that when the hidden factor dimension is 12, the system performs best on animation features. In terms of recommendation and search, the accuracy of the classification regression tree algorithm model is significantly higher than that of traditional collaborative filtering recommendation methods, and the recall rate also shows superiority. In addition, the system has optimized data management through dimensionality reduction technology, enabling low dimensional data to accurately reflect results and improving the efficiency of search, recommendation, and viewing. In practical applications, the stability and performance of the system have been verified, meeting the usage needs of teachers and students. Through classroom tests and analysis of student grades in animation teaching, it was found that the system can effectively enhance students' painting and directing skills, animation scope, and appreciation of animation. The satisfaction survey results of teachers and students also show that the system has been widely applied and praised in practical teaching.

However, in research based on big data, the quality and completeness of data are crucial. In practical applications, there may be issues such as missing, incorrect, or inconsistent data. This may lead to inaccurate or biased analysis results, thereby affecting the effectiveness of instructional design. Although big data fusion technology has achieved some successful applications in other fields, its application in animation media art teaching design is still in the exploratory stage. Therefore, there may be some uncertainty in the feasibility and stability of the technology. In order to improve data quality, future research will pay more attention to the process of data cleaning, validation, and integration. By adopting advanced data preprocessing techniques, errors and inconsistencies in the data can be identified and corrected, ensuring the accuracy of the analysis results. The system will adopt more robust data storage and backup mechanisms. Meanwhile, by introducing data auditing and monitoring mechanisms, data integrity issues can be promptly identified and addressed, ensuring data integrity and credibility.

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Advancing Human Action Recognition and Medical Image Segmentation using GRU Networks with V-Net Architecture

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Abstract—**Human Action Recognition and Medical Image Segmentation study presents a novel framework that leverages advanced neural network architectures to improve Medical Image Segmentation and Human Action Recognition (HAR). Gated Recurrent Units (GRU) are used in the HAR domain to efficiently capture complex temporal correlations in video sequences, yielding better accuracy, precision, recall, and F1 Score than current models. In computer vision and medical imaging, the current research environment highlights the significance of advanced techniques, especially when addressing problems like computational complexity, resilience, and noise in real-world applications. Improved medical image segmentation and human action recognition (HAR) are of growing interest. While methods such as the V-Net architecture for medical picture segmentation and Spatial Temporal Graph Convolutional Networks (ST-GCNs) for HAR have shown promise, they are constrained by things like processing requirement and noise sensitivity. The suggested methods highlight the necessity of sophisticated neural network topologies and optimisation techniques for medical picture segmentation and HAR, with further study focusing on transfer learning and attention processes. A Python tool has been implemented to perform min-max normalization, utilize GRU for human action recognition, employ V-net for medical image segmentation, and optimize with the Adam optimizer, with performance evaluation metrics integrated for comprehensive analysis. This study provides an optimised GRU network strategy for Human Action Recognition with 92% accuracy, and a V-Net-based method for Medical Image Segmentation with 88% Intersection over Union and 92% Dice Coefficient.**

Keywords—Human action recognition; medical image segmentation; grated rectifier unit; V-net architecture; neural network

I. Introduction

In the fields of computer vision and artificial intelligence, human action recognition concentrates on creating systems and techniques that can automatically recognize and comprehend human actions from video footage [1] [2]. Applications such as surveillance, augmented reality, healthcare, human-computer interaction, and sports analysis depend heavily on this form of technology [3]. The main goal is to make it possible for robots to comprehend human behaviour and react accordingly, promoting more logical and instinctive interactions between people and technology. In order to recognize human actions, motion patterns, postures, and gestures made by people in a video sequence must be examined and deciphered. This frequently entails the identification and tracking of important bodily components, such as limbs and joints, as well as the extraction of pertinent characteristics that are indicative of certain movements [4]. The intricacies of the temporal and spatial dynamics of human behaviours may be captured and learned through the use of methods such as machine learning, especially deep learning. The heterogeneity in human motions across various people, contexts, and viewing situations is one of the main issues in human action recognition [5]. To be useful in a variety of real-world situations, robust techniques need to be able to generalize their learning to account for these variances. Large datasets including labelled action sequences are frequently used by researchers to train algorithms that can accurately identify a broad variety of activities.

Human action recognition may be done primarily using two methods: 2D-based and 3D-based. 2D-based techniques only take into account spatial information when recognizing actions; all other information is taken from individual video frames [6]. However, by examining the motion sequences over a number of frames, 3D-based techniques make use of both temporal and spatial information. Enhancing identification accuracy and capturing the dynamic character of actions are the main benefits of the latter technique [7]. Recognition of human actions has many real-world uses. It improves safety protocols in video surveillance systems by automatically identifying suspicious or unusual activity [8]. It can help with diagnosis and rehabilitation in the medical field by tracking and evaluating patient activities. It aids coaches and analysts in sports analysis by enabling them to assess the performance of participants and plan more skillfully. Furthermore, it makes it possible for machines to react to gestures and orders from humans, resulting in natural and straightforward user interfaces for human-computer interaction [9]. With the use of increasingly complex algorithms, better sensor innovations, and increased processing power, human action recognition keeps developing as technology progresses. Human action recognition is an important aspect in the creation of artificially intelligent machines that better comprehend and interact with the natural world. Ongoing research in this topic tries to solve issues relating to immediate analysis, scalability, and reliability [10] [11] [12].

A crucial area of study in the larger study of health care imaging is medical image segmentation, which focuses on identifying and separating certain structures or areas of interest from medical pictures. To enable a more thorough examination of different tissues, organs, or structures, this technique entails dividing a picture into meaningful and functionally relevant portions [13]. Partitioning medical images is essential for planning treatments, making diagnoses, and tracking the course of illnesses. Medical image segmentation's main goal is to give precise and accurate delineation of diseased areas or anatomical features in pictures [14]. Peptide emission tomography (PET), MRI, ultrasound, and CT are among the imaging modalities that use this technique. The creation of strong segmentation algorithms is essential for effective clinical assessments since every technique has different obstacles, such as variations in contrast, resolution, and noise [15]. The intrinsic complexity and diversity of human anatomy is one of the primary obstacles in separating medical images. The size, shape, and design of organs or other structures may vary throughout people, and diseased states may make the segmentation process even more difficult [16]. Deep learning computations, machine learning, and sophisticated processing of images approaches are used by investigators as well as practitioners to solve these issues [17]. Particularly with regard to recognizing complex patterns in medical pictures and learning centralized characteristics, deep learning has proven remarkably effective. Medical separation of images has several uses and affects different facets of health care.

Radiologists and medical professionals can more precisely detect and measure anomalies, such as tumours, lesions, or irregularities in organs, with the use of segmentation [18]. Proper segmentation is essential to target specific areas with minimal harm to surrounding healthy tissues during treatment planning, particularly in radiation treatments and surgery. Furthermore, longitudinal studies, which need medical image segmentation to follow therapy response and illness development over time, depend on it [19]. From conventional, rule-based techniques to more advanced, data-driven processes, medical imaging segmentation has evolved throughout time. Convolutional neural networks (CNNs) and other deep learning topologies are examples of machine learning systems that have demonstrated significant potential in automating and enhancing the accuracy of segmentation jobs [20]. Moreover, the use of artificial intelligence into medical picture segmentation not only improves productivity but also creates opportunities for customized treatment plans and personalized medication. Medical picture segmentation research is still ongoing, with particular issues being addressed include managing big datasets, guaranteeing robustness across different patient groups, and enhancing real-time processing capabilities [21]. Medical image segmentation continues to be essential to the creation of cutting-edge medical and diagnostic devices as technological develops, improving the results for patients and care.

The key contributions of this study are as follows:

- The research contributes a robust framework for Human Action Recognition by utilising Gated Recurrent Units (GRUs) with an advanced gating mechanism. This results in superior accuracy, precision, recall, and F1 Score when compared to existing models.
- The study offers an effective V-Net architecture-based approach for medical image segmentation. The model achieves impressive Dice Coefficient, Intersection over Union (IoU), recall, and F1 Score, pushing the state-of-the-art in precise structure delineation. It also performs exceptionally well in capturing spatial dependencies and complex characteristics in volumetric medical pictures.
- The integration of Min-Max normalization ensures equitable feature contributions, particularly valuable when dealing with datasets containing features of varying scales. Furthermore, by applying the Adam optimizer, the Human Action Recognition and Medical Image Segmentation models perform better, exhibiting flexibility in the face of different gradients and the ability to process big datasets with high-dimensional feature spaces.
- The study highlights the investigation of attention mechanisms in Human Action Recognition and the use of transfer learning and new loss functions in Medical Image Segmentation to further improve model performance and generalisation across various datasets. These valuable insights could lead to further research endeavours.

The research began with a preliminary study of the literature review and research gasps, which are presented in Section II. The research was performed according to the proposed research methodology and is presented in Section III. The results of the study are presented and discussed in Section IV. Finally, the conclusions and limitations are presented in Section V.

II. Related Works

The capacity of skeleton-based action detection to record human body motions using 3D skeletal joint data has attracted a lot of attention in the field of computer vision. One effective approach for simulating the spatiotemporal relationships in such data is the Spatial Temporal Graph Convolutional Network (ST-GCN) [22]. An extensive investigation of the use of ST-GCNs for skeleton-based action recognition is presented in this research. The suggested model makes use of both temporal and spatial graph convolutions to efficiently represent the complex interactions that develop between skeletal joints over time, allowing for reliable action identification in a variety of contexts. Although ST-GCNs have proven to be useful, one significant limitation is their susceptibility to noise and errors in skeletal joint data. The quality of the input data in real-world applications might be impacted by noise from depth sensors, occlusions, or errors in joint localization. Such noise may be too much for ST-GCNs to manage, which might result in subpar performance and possibly incorrect classifications. Resolving this constraint is essential to improving the model's resilience in real-world scenarios, particularly when handling noisy or incomplete skeleton data that is frequently encountered. Prospective research avenues may concentrate on devising techniques to enhance the robustness of ST-GCNs against noisy input, guaranteeing dependable action identification under demanding circumstances.

Zhu et al. [23] research presents a novel method for action identification in video data: Hidden Two-Stream Convolutional Networks (HTSCNs). The spatial and temporal streams that make up the two-stream architectural have shown to be successful in gathering both appearance and motion data. Nevertheless, the efficient fusion of both streams to extract distinct characteristics is frequently a difficulty for classic two-stream networks. A hidden fusion mechanism is added to HTSCNs, enabling more contextually aware and adaptable fusing of temporal and spatial data. The technique that has been suggested performs better at identifying intricate activities by utilizing the complimentary data from both sources. Although HTSCNs provide improvements in the fusion of temporal and spatial data, the hidden fusion mechanism's added computing complexity may be a disadvantage. During training and inference, the extra layers or procedures added for adaptive fusion may require more processing power. This may restrict the framework's usefulness in situations when resources are few or real-time. When implementing HTSCNs in environments with limited computing resources, it is important to balance the enhanced fusion capacities with the effectiveness of computation. In order to preserve the advantages of the concealed fusion process while reducing the computational cost and guaranteeing wider usage and accessibility of the suggested technique, future research might investigate optimizations or other approaches.

The sophisticated movement detection system presented in this study makes use of Long-Term Recurrent Convolution Networks (LTRCNs) [24], a hybrid design that combines the advantages of convolutional and recurrent neural networks. In interacting with computers, gesture recognition is essential, and the suggested LTRCN model tackles the difficulties in capturing the temporal and spatial connections in gesture sequences. The model achieves advanced performance in recognizing a selection of complicated gestures by utilizing convolutional methods to capture spatial data and recurrent layers to include long-term memory. The efficacy of the LTRCN is demonstrated by its positive outcomes in a variety of situations in real life, such as recognizing signs and human-computer interface exchanges. The LTRCN's higher processing requirements, especially during training, might be a disadvantage considering its outstanding performance. Higher resource needs and longer training periods may result from the incorporation of repetitive layers, which describe temporal relationships across lengthy sequences. This might provide problems in instances where distribution on devices with limited resources or real-time processing are critical. For real-world use, it is important to address the computing cost while maintaining the accuracy of the model. To increase the viability of implementing the LTRCN in actual, limited resources contexts, future research might concentrate on improving training efficiency, investigating model compression approaches, or creating hardware-accelerated systems.

The unique ViT-V-Net method for unsupervised dimensional imaging identification is presented in this research. It makes use of the Vision Transformer (ViT) structure [25]. Optimizing the combination of pictures from distinct sources or time periods is a crucial job in many clinical applications such as medical image registrations. In order to extract strong features for precise registration without requiring labelled training data, ViT-V-Net makes use of the self-attention mechanism built into ViT to capture long-range relationships in volumetric data. This approach has the potential to improve medical image assessment and diagnosis because of its better effectiveness in regarding accuracy and adaptability. The potential disadvantage of ViT-V-Net is its computational cost, even if it offers an attractive option for unsupervised volumetric medical picture registration. This is because Vision Transformer designs are complicated. The volumetric medical data analyzing requires managing huge input sizes, which can result in higher memory and computing needs. ViTs are notorious for being parameter-intensive. Specifically in actual time or limited resources clinical situations, the scalability of ViT-V-Net for big health data sets and the effectiveness during inferences are issues that require careful study. In order to assure ViT-V-Net's effectiveness for healthcare contexts with diverse computing resources, future study may concentrate on optimizing the computational effectiveness of the system and investigating acceleration using hardware or model compression approaches.

Liver and tumour segmentation on computed tomography (CT) images are addressed by this study, which presents a unique technique to medical picture segmentation. Using a 2.5D Fully Convolutional Neural Networks (FCNN) architecture [26], the suggested approach makes use of boundary loss. Utilizing both spatial and volumetric contexts to enhance segmentation accuracy, the 2.5D method integrates 2D and 3D data. The model's capacity to accurately define object borders is improved by the addition of boundary loss, which is important for medical imaging applications. Results from experiments using CT datasets reveal how well the suggested method works to segment liver and tumour structures with high accuracy and detail, indicating its potential to improve clinical diagnostics. The Boundary Loss-Based 2.5D FCNN technique has a potential downside in that it is sensitive to fluctuations in data quality and imaging artifacts that are frequently found in medical pictures, while its optimistic effectiveness in segmenting. Noise, artifacts, and inefficiencies in CT scans might compromise the model's resilience and ability to generalize to a variety of datasets. It is imperative to tackle this obstacle in order to implement the suggested approach in various medical imaging contexts. In order to strengthen the algorithm's dependability in practical healthcare settings, further research should examine ways for enhancing the model's resistance to noise and artifacts, such as using data augmentation tactics or creating sophisticated preparation approaches.

Y. Chen et al. [27] research, a conditional random field (CRF) and deep learning are used to propose an effective two-step method for liver and tumour segmentation on abdominal CT images. In the first stage, the liver and tumour areas are coarsely delineated with the use of a deep learning algorithm for initial segmentation. The segmentation is then further refined by enhancing the consistency of space and integrating historical data using a conditional random field. The suggested technique successfully and efficiently segments the data, as shown by the abdominal CT datasets. The aforementioned two-step procedure exhibits the potential of CRF to improve precision in medical image analysis by utilizing not just the structured modelling skills of CRF for enhanced segmentation results, but also the capability of deep computing for extracting features. The conditionally random field in the refining stage adds additional processing complexity, which might be a disadvantage even though the two-step strategy appears promising. The effectiveness of the method for segmentation may be impacted by the increased computing cost, especially in situations when immediate analysis is essential, such during critical circumstances or surgical procedures. For real-world implementation, it is crucial to strike a compromise between increased segmentation accuracy and computing efficiency. Subsequent investigations might examine optimizations, parallelization tactics, or substitute improvement methods to reduce processing requirements while preserving the superior segmentation attained via the integration of deep learning and CRF methodology.

The new methods for addressing different computer vision and imaging-related problems are presented in these publications. While conceding their susceptibility to noise, the first study highlights the efficiency of skeleton-based action identification utilizing Spatial Temporal Graph Convolutional Networks (ST-GCNs). In order to recognize actions, the second one presents Hidden Two-Stream Convolutional Networks (HTSCNs), which exhibit better performance but acknowledge higher computational cost. The third paper investigates gesture recognition using Long-Term Recurrent Convolution Networks (LTRCNs), which show promise but also have greater processing costs. The fourth study looks into volumetric medical image registration without supervision using Vision Transformer (ViT). It performs better but raises concerns about computational complexity. Lastly, a two-step conditional random field and deep learning approach to liver and tumour segmentation on CT images demonstrates effectiveness despite a greater processing cost. Overall, these studies provide valuable insights into advanced techniques for diverse applications, but they also highlight the on-going challenge of finding a compromise between computer performance and efficiency.

The present research environment emphasizes the importance of sophisticated techniques in computer vision and medical imaging, particularly when dealing with issues like noise, computational complexity, and robustness in real-world applications. There is an increasing interest in enhancing human action recognition (HAR) and medical image segmentation. While approaches like Spatial Temporal Graph Convolutional Networks (ST-GCNs) for HAR and the V-Net architecture for medical picture segmentation have showed promise, they are limited by factors such as noise sensitivity and processing need. These constraints limit their efficacy in real-world applications with noisy data and limited processing resources [23].

As a result of this, the proposed method's overarching problem is to create a framework that uses advanced neural network architectures, such as Gated Recurrent Units (GRU) for HAR and V-Net for medical image segmentation, to improve the robustness, accuracy, and efficiency of these tasks in real-world settings. This involves minimizing the impact of noise in skeletal joint data for HAR, controlling the computational complexity of fusion mechanisms in HAR models such as Hidden Two-Stream Convolutional Networks (HTSCNs), handling processing demands in Long-Term Recurrent Convolution Networks (LTRCNs) for gesture recognition, maximizing computational efficiency in Vision Transformer (ViT) for volumetric medical image registration, and enhancing resilience to noise and artifacts in liver and tumor segmentation on CT images through the use of 2.5D Fully Convolutional Neural Networks (FCNN) and conditional random field (CRF) techniques [27] [25].

III. Proposed Mechanism of HAR and Image Segmentation

The proposed approach integrates min-max normalization as a preprocessing step to standardize input data, ensuring consistent scales for subsequent tasks. In the domain of Human Action Recognition, Gated Recurrent Units (GRU) is employed to capture temporal dependencies, enabling effective modelling of sequential human actions. For Medical Image Segmentation, the proposed method utilizes the V-net architecture, a 3D convolutional neural network designed for precise delineation of structures in medical images. The optimization process is facilitated by the Adam optimizer, enhancing convergence during model training. Performance evaluation involves metrics such as accuracy, precision, recall, and F1-score to comprehensively assess the effectiveness of the proposed approach in achieving accurate and robust results in both human action recognition and medical image segmentation tasks. Fig. 1 illustrates the workflow of the proposed mechanism.

The proposed solution introduces novel advancements in both Human Action Recognition (HAR) and Medical Image Segmentation by leveraging Gated Recurrent Units (GRU) and the V-Net architecture, respectively. In contrast to existing frameworks like Spatial Temporal Graph Convolutional Networks (ST-GCNs) for HAR, the utilization of GRUs enables efficient capture of complex temporal correlations in video sequences, addressing long-range dependencies and the vanishing gradient problem. This enhances the model's accuracy and reliability in action detection tasks. Similarly, in Medical Image Segmentation, the V-Net architecture offers superior precision in identifying structures of interest compared to traditional convolutional neural networks (CNNs) or Fully Convolutional Neural Networks (FCNNs). By integrating these advanced techniques, the proposed solution provides a comprehensive approach to improving performance and resilience in both HAR and Medical Image Segmentation tasks, offering significant advancements over existing methodologies.

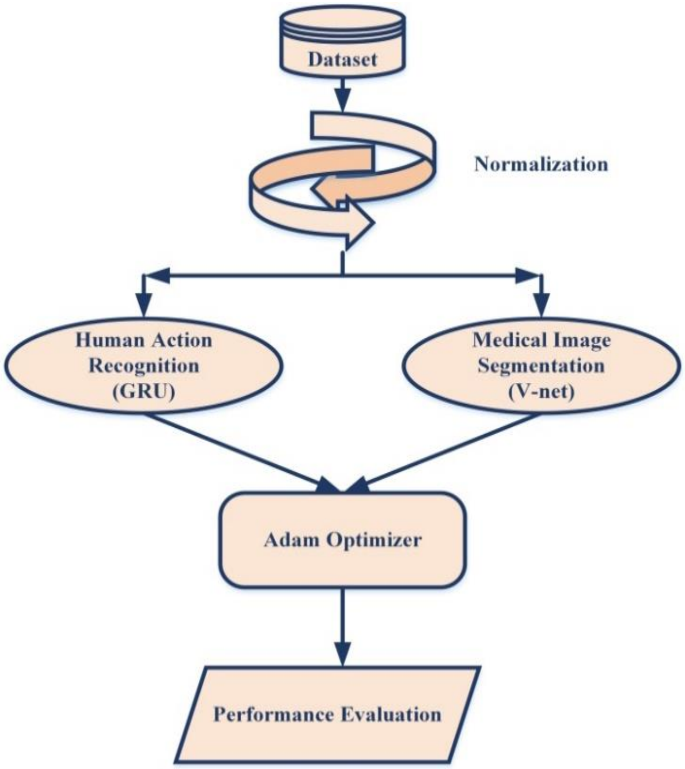
Dataset
Normalization
Human Action Recognition (GRU)
Medical Image Segmentation (V-net)
Adam Optimizer
Performance Evaluation

Fig. 1. Mechanism of human action recognition and medical image segmentation.

A. Min-Max Normalization

A data preparation method called min-max normalization is used to rescale numerical characteristics within a certain range, usually between 0 and 1. This technique guarantees that every feature contributes equally to the model training process, which makes it very helpful when working with datasets that contain features of varying sizes. For Min-Max normalization, (1) is provided:

$$X_{Norm} = \frac{X_{max}-X_{min}}{X_{min}} \tag{1}$$

Where, X_{Norm} is the normalized value of the feature, X is the raw data, X_{min} is the minimum value of the feature in dataset and X_{max} is the maximum value of the feature in the dataset.

B. Human Action Recognition with GRU

A computer vision problem known as Human Action Recognition (HAR) entails recognizing and categorizing human actions from video footage. It may be used in many different domains, including as healthcare, human-computer interaction, and surveillance. Recurrent neural networks (RNNs), of which Gated Recurrent Units (GRUs) are a particular kind of RNN architecture, are a common method for handling HAR. One sort of recurrent neural network that is particularly good at identifying sequential relationships in data is the Gated Recurrent Unit (GRU). GRUs are equipped with a more advanced gating mechanism than typical RNNs, which helps them deal with long-range dependencies and solve the vanishing gradient issue [28]. For processing sequential input, such as video frames, in the framework of human action detection, it makes GRUs particularly effective. The input to network infrastructure in the context of HAR with GRU is a series of video frames that depict a human activity. Every frame is considered a temporal step, and temporal relationships between successive frames are captured by the GRU as it analyses each frame individually. The primary benefit of employing GRUs is their capacity to preserve a hidden state that contains data from earlier frames, allowing the network to pick up on patterns in the temporal progression of activities. The input layer, the GRU layer, and the output layer are the three primary parts of the framework of a GRU-based HAR framework.

The sequential method video frames are sent into the input layer, and the GRU layer analyses those images while preserving a hidden state that contains temporal information. The final prediction, which indicates the acknowledged human action, is produced by the output layer. Backpropagation through time (BPTT) is used to modify the weights of the GRU network as it learns from labelled video sequences input into the model. Reducing the discrepancy between the actual truth classifications and the expected behaviours is the aim. Through this approach, the temporal dynamics of different human behaviours may be captured by the GRU. Researchers frequently use strategies like data augmentation, transfer learning, and attention processes to improve the efficiency of HAR with GRU. The technique of transfer learning entails pretraining the framework on a big dataset and optimizing it for the particular HAR task, whereas data augmentation is performing random modifications to the input data to improve the variety of training samples. By aiding the model in concentrating on pertinent segments of the input sequence, attention mechanisms enhance the model's capacity to identify critical details for action detection. In summary, Gated Recurrent Units are used in Human Action Recognition using GRU to identify temporal connections in sequential video data. This framework is a potent tool for jobs requiring the interpretation of dynamic activities from video streams because of its GRU-based design, which allows it to learn and recognize patterns in the temporal development of human behaviours. Fig. 2 depicts GRU architecture.

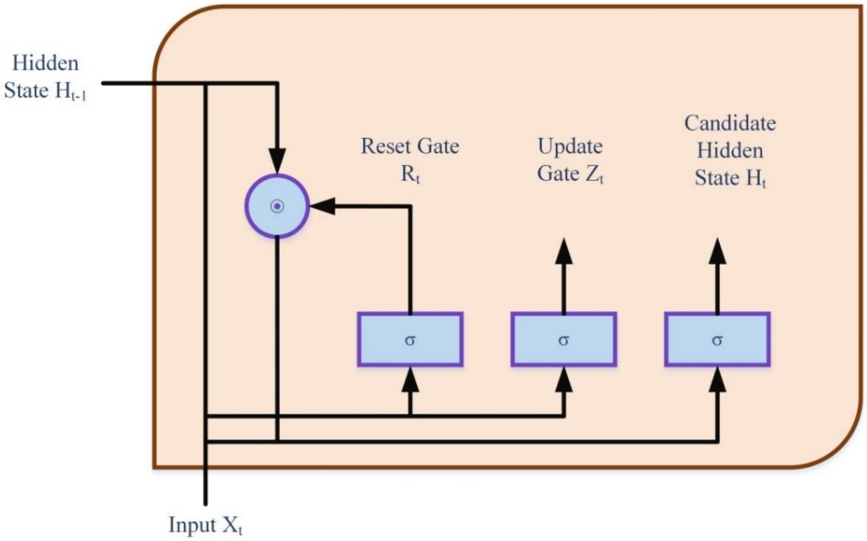

Fig. 2. GRU Architecture.

C. Sequence Modelling with GRU

An RNN type called a GRU is made specifically to identify and represent dependencies in sequential data. They work especially well with long-range interdependence, which is a critical component in comprehending how people behave over time. The update gate, reset gate, and hidden state are a GRU's essential parts. Here is how the reset gate r_t and update gate z_t are computed in (2) and (3):

$$z_t = \sigma(W_z * [h_{t-1}, x_t]) \quad (2)$$

$$r_t = \sigma(W_r * [h_{t-1}, x_t]) \quad (3)$$

Where, the input at the current time step is x_t, while the hidden state at the previous time step is h_{t-1}. The sigmoid activation function is σ.

1) Candidate hidden state calculation: The reset gate r_t and the current input x_t are used to calculate the candidate hidden state $\tilde{h}_t$ is expressed i (4):

$$\tilde{h}_t = \tan h(W_h * [r_t \odot h_{t-1}, x_t]) \quad (4)$$

Here, ⊙ denotes element-wise multiplication.

2) Update hidden state: The candidate hidden state $\tilde{h}_t$, the preceding hidden state h_{t-1}, and the update gate z_t are used to update the hidden state h_t is expressed in (5):

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (5)$$

3) Action recognition using GRU: A video clip is supplied frame by frame into the GRU model for HAR. Action categorization uses the final hidden state h_T obtained by analyzing the whole sequence. The one way to accomplish this is to transmit h_T across a fully linked layer and then a softmax activation function in (6):

$$Action\ Score = softmax(W_{out} * h_T + b_{out}) \quad (6)$$

Where, W_{out} and b_{out} represent the weight matrix and bias vector of the output layer, respectively. When using GRUs for Human Action Recognition, video sequences are processed using a recurrent neural network. The GRU records temporal relationships, and action categorization is done using the final hidden state. Optimizing the parameters to minimize a selected loss function is the process of training the algorithm.

D. Medical Image Segmentation with V-net

V-Net Medical Image Segmentation is an advanced method that uses deep learning techniques to identify and categorize structures of interest in medical pictures. Three-dimensional medical picture segmentation tasks are a good fit for V-Net, an extension of the U-Net architecture that is particularly made for volumetric data. In order to achieve precise and significant segmentation in the field of medical imaging, V-Net's primary strength is its capacity to capture spatial dependencies and minute features in medical pictures. In the V-Net architecture [29], structured characteristics are captured by the encoder using a sequence of 3D convolutional layers, and the segmented output is reconstructed by the decoder using 3D deconvolutional layers. Skip connections, which link matching encoding and decoding layers and aid in the retention of spatial information, define the architecture. This capability is especially useful for applications involving the segmentation of medical images where accurate localization of structures is crucial. Reversed linear unit (ReLU) activation functions, batch normalization, and three-dimensional convolutions are the processing steps that the input medical picture passes through along the encoding path. With the help of these layers, which extract hierarchical characteristics at various sizes, the incoming data is richly represented. During the encoding-decoding process, the skip connections make sure that minute information are kept. Three-dimensional deconvolutions are used in the decoding path to up sample feature maps. Each decoding layer also includes batch normalization, ReLU activation, and three-dimensional convolutions, just like in the encoding path. In order to concatenate the high-resolution feature maps from the encoding path and facilitate the reconstruction of the segmented output with better localization accuracy, skip connections are essential during the decoding phase.

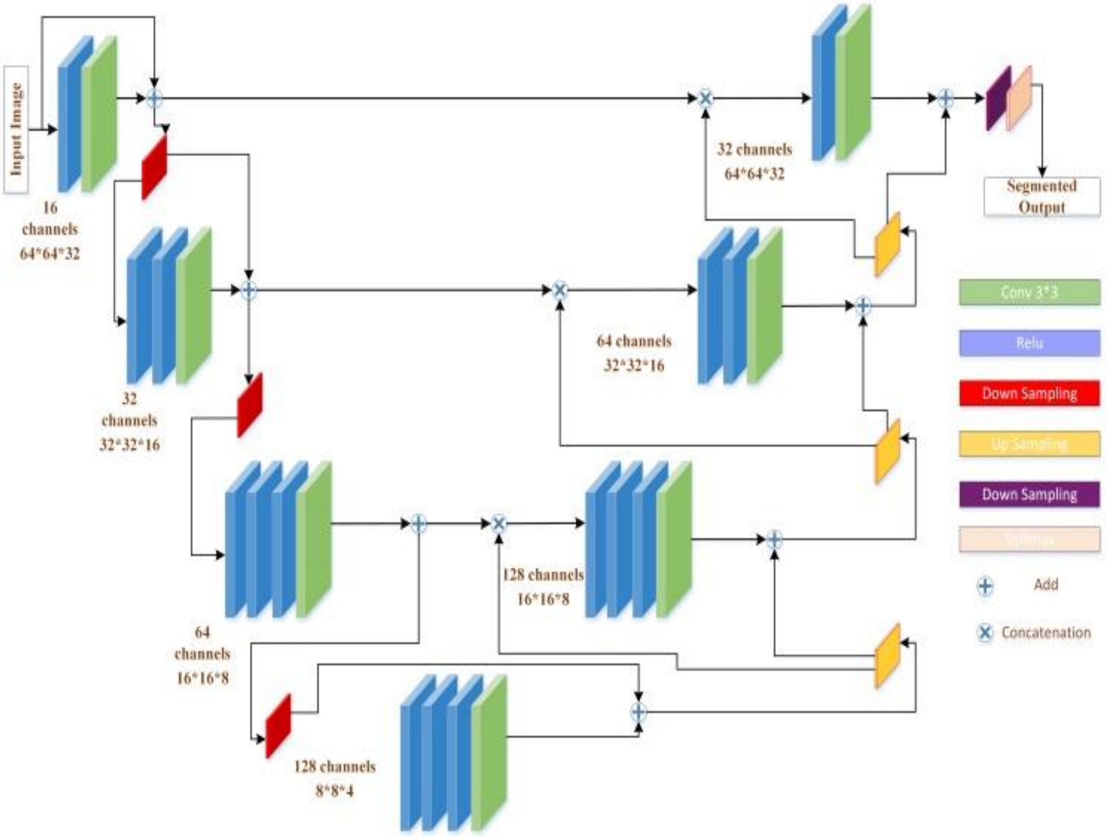

Fig. 3. V-Net architecture.

The segmentation map is usually generated via a 1x1x1 convolution in the last layer of the V-Net. To get probability scores for each class, a softmax activation function is frequently used. This allows the model to classify each voxel in the picture to the correct structure or class. Depending on the particular segmentation job, a loss function such as cross-entropy loss or dice coefficient loss may be selected during training. The V-Net model is trained on annotated medical picture datasets with ground truth segmentation masks during the training phase. The optimization method, usually Adam or SGD, minimizes the selected loss function by iteratively adjusting the model's parameters. Furthermore, methods like class-weighted loss or data augmentation may be used to resolve class imbalance, which is common in medical picture segmentation tasks. Using previously unknown medical pictures, the trained V-Net is utilized during the inference phase to create segmentation maps that identify and highlight structures of interest. To improve the segmentation result, post-processing techniques like thresholding might be used. All things considered, V-Net is a reliable method for medical picture segmentation that advances the area of medical imaging's therapeutic and diagnostic applications. Specifically created for volumetric medical picture segmentation, V-Net is an expansion of the U-Net architecture. Fig. 3 depicts V-Net Architecture and its design is made up of skip connections in an encoder-decoder configuration. Mathematically, batch normalization, ReLU activation functions, and a sequence of 3D convolutions are used in the encoding process is expressed in (7):

$$f_{encoder} = RELU\left(BatchNorm\left(Conv3D(x)\right)\right) \tag{7}$$

Here, $f_{encoder}$ represents the feature map, x is the input image, $Conv3D$ denotes the 3D convolution operation, and $BatchNorm$ represents batch normalization. The V-Net design relies heavily on skip connections, which let the model maintain fine-grained information during the encoding-decoding procedure. The skip link may be expressed mathematically as follows in (8):

$$Skip = Concatenate(x, f_{enc}) \tag{8}$$

Here, $Concatenate$ merges the input image x with the feature map f_{enc}. The decoding path entails processing by using decoding layers and more samples the feature maps using 3D deconvolutions in (9):

$$f_{decoder} = ReLU\left(BatchNorm\left(Conv3DTanspose(Skip)\right)\right) \tag{9}$$

Here, $Conv3DTanspose$ represents the 3D deconvolution operation. The segmentation map is generated by the last layer using a softmax activation function and a 1x1x1 convolution in (10):

$$SegMap = Softmax\left(Conv1 \times 1 \times 1(f_{dec})\right) \tag{10}$$

For every class, probability scores are provided by the softmax activation. The segmentation task influences the loss function selection. Frequently employed in medical picture segmentation, dice coefficient loss is described as follows in (11):

$$Dice = \frac{2 \times Intersection(G,S)}{Union(G,S)} \tag{11}$$

Here, G is the ground truth segmentation mask, and S is the predicted segmentation mask. For precise medical picture segmentation, V-Net combines encoding, decoding, skip connections, and a softmax output layer. During inference, the model is applied to unseen pictures for segmentation, with optional post-processing steps for improvement. Training entails optimizing parameters using a chosen loss function.

E. Adam Optimizer for HAR and Image Segmentation

1) Adam optimizer for human action recognition: The Adam optimizer is essential to the training of the neural network in Human Action Recognition (HAR). Recurrent neural networks (RNNs), such as the Gated Recurrent Unit (GRU), are frequently used in sequential data processing. With HAR, temporal relationships in video sequences are captured, and training over a variety of action sequences is made more efficient because to Adam's adjustable learning rates. When improving the model features during training, the optimizer may constantly modify the step sizes. This is especially useful for HAR jobs, where the complexity and length of several activities might differ. The model integrates effectively, reflecting both short-term and long-term correlations in human activities, thanks to the optimizer's flexibility in responding to the diverse gradients of various acts. Smooth parameter updates are made possible by Adam's first and second moment estimations, which are exponential moving averages. These moving averages give the optimizer assistance in navigating the complex dynamics of human motions in the context of HAR, where the detection of actions depends on subtle temporal patterns. The bias correction feature in Adam also helps to maintain the stability and dependability of the training procedure by preventing unwarranted biases in parameter estimations from being introduced during the early stages of training. However, by rapidly adapting to the temporal features of actions and guaranteeing steady convergence during the optimization process, the Adam optimizer improves the training accuracy of frameworks for Human Action Recognition.

2) Adam optimizer for medical image segmentation: The flexibility and effectiveness of the Adam optimizer make it a good candidate for Medical Image Segmentation applications, such as those using topologies like V-Net, because it can handle big datasets with extremely dimensional feature spaces. Complex spatial relationships are involved in image segmentation, and Adam's adaptive learning rates help deep neural networks be trained for reliable segmentation. 3D volumetric data is processed by the architecture in V-Net-based medical picture segmentation. The optimizer [30] may separately adjust characteristics for various spatial dimensions thanks to the adaptive learning rates, which guarantees that the model accurately represents the subtleties and spatial connections present in the health-related images. Adam's exponential fluctuations facilitate the optimization process' smooth convergence, which enables the model to pick up on and adjust to intricate patterns found in medical imagery. In medical picture segmentation, where retaining accuracy in early training phases is critical for exact segmentation, Adam's bias correction is especially relevant. The optimization process is made more solid and dependable by the correction terms, which guarantee that the optimizer begins with objective estimations. For problems involving Medical Image Segmentation, where stability during training, effective convergence, and flexibility to spatial dependencies are critical, the Adam optimizer is a good fit. In addition to exponentially average movements and bias correction, the flexible learning rate technique makes the development of deep neural networks more successful in terms of producing dependable and accurate medicinal image segmentation.

Algorithm I: Adam Optimizer

```
Step 1:  Initialize the parameters of the segmentation model, including the weights and biases, and the Adam optimizer hyper parameters $(\alpha, \beta_1, \beta_2, \epsilon)$.
Step 2:  Initialize the first moment estimate $(m_t)$ and the second moment estimate $(v_t)$ to 0.
Step 3:  For each iteration $t$:
         a. Compute the gradient of the loss with respect to the segmentation model parameters $\nabla_0 Loss$.
         b. Update the first moment estimate $(m_t)$ and the second moment estimate $(v_t)$ using exponential decay:
            $m_t = \beta_1 * m_{t-1} + (1 - \beta_1) * \nabla_0 Loss$
            $v_t = \beta_2 * v_{t-1} + (1 - \beta_2) * (\nabla_0 Loss)^2$
Step 4:  Perform bias correction to account for initialization bias in the moments:
            $\widehat{m}_t = \frac{m_t}{1 - \beta_1^t}$
            $\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$
Step 5:  Update the segmentation model parameters using the bias-corrected estimates and the learning rate:
            $\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\hat{v}_t + \epsilon}} * \widehat{m}_t$
Step 6:  Repeat the process for a specified number of iterations or until convergence.
```

Algorithm 1 describes the Adam Optimizer. These actions together form the Adam optimization algorithm in both situations, which offers a flexible and effective method of updating model parameters when training medical image segmentation and human action recognition systems. The Adam optimizer performs best in these situations when hyper parameters are adjusted and convergence is monitored.

IV. RESULTS AND DISCUSSION

A Python tool has been developed to carry out min-max normalisation, apply V-net for medical image segmentation, use GRU for human action detection, and optimise with the Adam optimizer. Performance assessment metrics have been included for thorough examination. Robust approaches are employed in the research for both model optimisation and evaluation, namely, Medical Image Segmentation using the V-Net architecture and Human Action Recognition (HAR) with

GRU networks. Min-Max normalisation rescales numerical attributes between 0 and 1 to guarantee equal feature contributions. The GRU-based HAR framework achieves noteworthy accuracy metrics of 92%, precision of 93%, recall of 91%, and an F1 Score of 92% by utilising the advanced temporal analytic capabilities of GRUs to identify sequential patterns in video data. A Dice Coefficient of 92%, Intersection over Union (IoU) of 88%, recall of 94%, and an exceptional F1 Score of 96% demonstrate the superior performance of the V-Net-based Medical Image Segmentation. Additionally, the Adam optimizer is important for improving the training efficiency of the Medical Image Segmentation and HAR models. It can handle huge datasets with high-dimensional feature spaces and adjust to different gradients in action sequences. The study results highlight how well the suggested approaches progress the fields of medical picture segmentation and HAR.

A. Performance Evaluation

1) Performance for human action recognition: For comparison, the following evaluation criteria were used: recall, F1-score, precision and accuracy. These parameters were used to assess the model. These are depicted below:

2) Accuracy: The prediction accuracy shown in (12) that is most frequently employed to assess classification performances is second hand to measure the classifier's general usefulness.

$$Accuracy = \frac{Tp' + Tn'}{Tp' + Tn' + Fp' + Fn'} \qquad (12)$$

3) Precision: The term precision is used to describe how well a group of outcomes agree with one another. Precision is usually defined as the difference between a set of outcomes and the set's arithmetic mean. It is shown in (13).

$$Precision = \frac{Tp'}{Tp' + Fn'} \qquad (13)$$

4) Recall: The purpose of recall analysis shown in (14) is to ascertain, under a certain set of assumptions, how several morals of an autonomous alterable effect a specific reliant on flexible. This procedure is applied within prearranged bounds that are dependent on single or additional input data variables.

$$Recall = \frac{Tp'}{Tp' + Fn'} \qquad (14)$$

5) F1 Score: Outcomes additional than estimate precision had better also be assessed when assessing the performance. The F1 score that is computed for this purpose evaluates the correlation among the information's expectant information and the classifier's predictions. It is shown in (15).

$$F1\ score = \frac{2Tp'}{2Tp' + Fp' + Fn'} \qquad (15)$$

6) Performance for medical image segmentation: For comparison, the following evaluation criteria were used: dice coefficient, intersection over unit (IoU), recall (14) and F1-score (15). These parameters were used to assess the model. These are depicted below:

7) Dice coefficient: The Dice Coefficient is a similarity metric for image segmentation that quantifies the overlap between the predicted and ground truth regions, calculated as twice the area of intersection divided by the total area of predicted and ground truth regions in (16).

$$Dice = \frac{2 * Area\ of\ Intersecion}{Total\ Area\ of\ Predicted + Total\ Area\ of\ Ground\ Truth} (16)$$

8) Intersection over Unit: The Intersection over Union (IoU) is a measure of the overlap between the predicted and ground truth regions in image segmentation, calculated as the area of intersection divided by the area of union in (17).

$$IoU = \frac{Area\ of\ Intersecion}{Area\ of\ Union} \qquad (17)$$

Fig. 4 shows the training accuracy of the Human Action Recognition model, which uses GRU networks for training, is a gauge of the model's effectiveness on the training dataset. It shows the proportion of cases that are properly categorised to all training samples. The training accuracy gives information about how well the model learns from the labelled data as repeatedly changes its parameters to minimise the loss function. Testing accuracy, on the other hand, evaluates how well the model generalises to fresh, untested data. It is computed by testing the model on an independent testing dataset that was not utilised for training. In order to enable generalisation to a variety of instances outside of the training data, a successful model usually has high training accuracy, which indicates effective learning from the training set, while retaining a comparable or slightly lower testing accuracy.

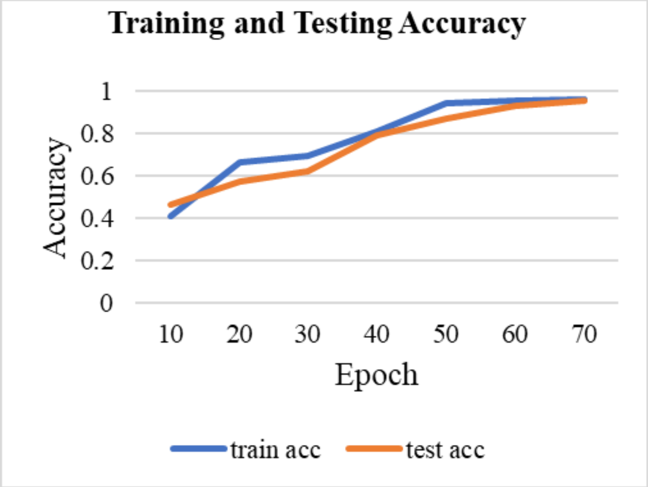

Fig. 4. Training and testing accuracy – GRU.

In order to assess the overall performance of the model and prevent overfitting or underfitting problems, it is imperative to keep an eye on both training and testing accuracy.

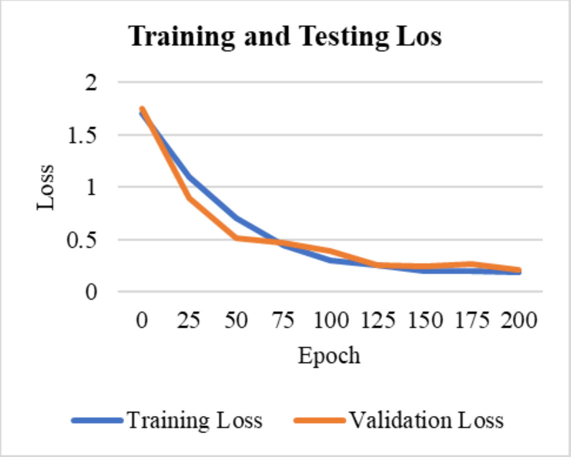

Fig. 5. Training and testing loss – GRU.

Fig. 5 shows the evaluation of a model's performance at various stages is largely dependent on the training and testing losses in the context of GRU networks and Human Action Recognition. The total error between the model's predictions and the ground truth labels on the training dataset is represented by the training loss. The goal is to minimise this loss while the model goes through training cycles by modifying the network's parameters. In contrast, testing loss is calculated using a different dataset that was not used for training the model. It functions as a crucial parameter for assessing how well the model generalises to fresh, untested data. To provide robustness and avoid overfitting, an efficient model has a comparable or slightly greater testing loss while exhibiting a low training loss, which indicates successful learning from the training set. In order to build a model that fits the training data effectively and performs consistently on fresh, varied instances, it is imperative to balance these losses.

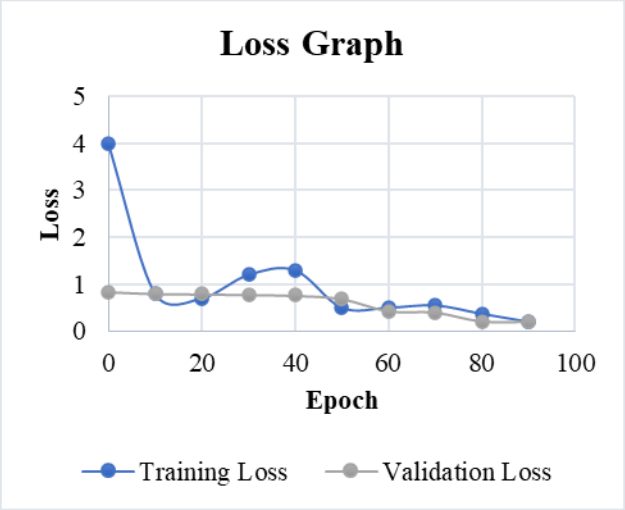

Fig. 6. Training and testing loss – V-net.

The trained V-Net is then evaluated on unseen data to assess its generalization performance, indicating its effectiveness in achieving low training and testing losses.

Fig. 6 shows the V-Net architecture is used for medical image segmentation by optimizing model parameters to minimize training loss. The model is trained with input medical images, and the difference between predicted and ground truth is computed as the training loss. The optimization process modifies the network's weights to reduce this loss, improving the model's ability to accurately segment anatomical structures.

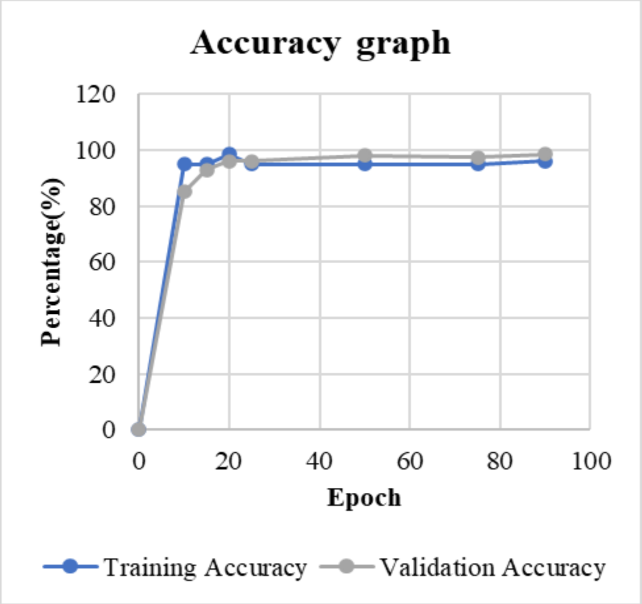

Fig. 7. Training and testing accuracy – V-net.

Fig. 7 shows Training and Testing Accuracy – V-net. The V-Net architecture is used for medical image segmentation, with training accuracy assessing the model's performance on the training dataset. It measures the proportion of correctly segmented pixels compared to the total number of pixels. Testing accuracy evaluates the model's generalization capability on new, unseen medical images, providing insights into its overall performance and potential for real-world applications. High training and testing accuracies indicate the V-Net's proficiency in accurately segmenting structures within medical images.

B. Findings from the Proposed Model

Table I describes the human action recognition with GRU. The model's effectiveness in the field of GRU networks-based human action recognition is measured by a number of measures. The achieved accuracy of 92% signifies the percentage of correctly identified actions out of all predictions made by the GRU-based model. The remaining 8% could represent misclassifications or instances where the model failed to accurately recognize human actions. Possible factors contributing to this error rate could include variability in human movement patterns, occlusions in the video data, or limitations in the training data representation. Precision, at 93%, indicates the model's ability to correctly identify affirmative examples (true positives) among all instances predicted as positive. This means that out of all actions predicted by the model, 93% were actually true positive cases. The remaining 7% could represent false positives, where the model incorrectly classified actions as positive.

TABLE. I HUMAN ACTION RECOGNITION WITH OPTIMIZED GRU

Metrics	Percentage (%)
Accuracy	92
Precision	93
Recall	91
F1 Score	92

With a recall rate of 91%, the model demonstrates its capability to capture all true positive cases among the total actual positive instances present in the dataset. This implies that out of all human actions that occurred in the video data, the model successfully identified 91% of them. The remaining 9% could represent instances of missed detections or false negatives, where the model failed to recognize certain actions. The F1 Score, which is a harmonic mean of precision and recall, achieves a balanced score of 92%. This indicates that the model maintains a stable performance by achieving a good balance between minimizing false positives (as reflected in precision) and minimizing false negatives (as reflected in recall). The F1 Score provides a comprehensive measure of the model's effectiveness in accurately identifying human activities while considering both precision and recall simultaneously.

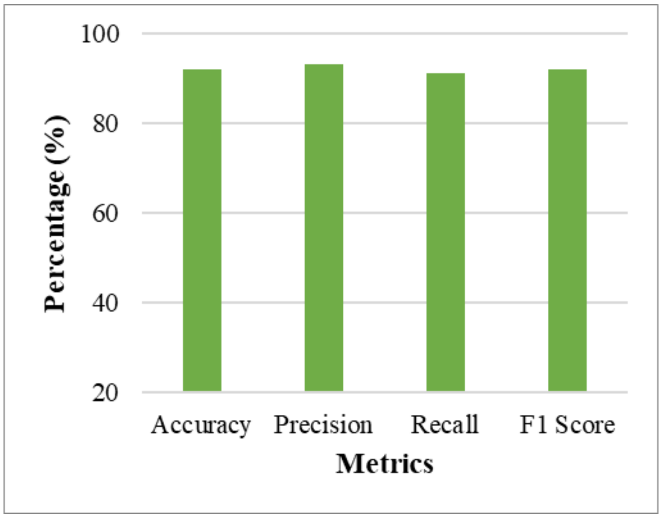

Fig. 8. Metrics of the proposed model.

Fig. 8 represents the metrics of the proposed model in graphical representation. The metrics for the proposed model showcases strong performance, with an accuracy of 92%, indicating the overall correctness of predictions. Precision at 93% reflects the model's ability to minimize false positives, while recall at 91% indicates its capacity to capture a substantial proportion of true positives. The balanced F1 score of 92% further underscores the model's effectiveness in achieving a harmonious trade-off between precision and recall.

Table II describes the Medical Image Segmentation with Optimized V-net. The model's effectiveness in medical picture segmentation using the optimised V-Net architecture is shown by the performance measures. The Dice Coefficient of 92% indicates the degree of overlap between the segmentation masks generated by the V-Net model and the ground truth masks. This high value suggests that 92% of the segmented areas from the model align well with the actual anatomical structures present in the medical images. The Intersection over Union (IoU) metric, reported at 88%, represents the ratio of the intersection area to the union area between the predicted and ground truth segmentation masks. An IoU of 88% implies that the V-Net model accurately delineates the boundaries of anatomical structures in the medical images, with a substantial overlap between the predicted and ground truth regions. With a recall measure of 94%, the V-Net model demonstrates its ability to effectively capture true positive cases, indicating a high sensitivity to identifying relevant anatomical components in the medical images. A recall of 94% suggests that the model successfully identifies 94% of the actual anatomical structures present in the medical images. The F1 Score, which balances precision and recall, reaches an impressive value of 96%. This high F1 Score underscores the V-Net model's exceptional performance in precisely identifying anatomical components in medical images while maintaining a harmonious balance between minimizing false positives and false negatives.

TABLE. II MEDICAL IMAGE SEGMENTATION WITH OPTIMIZED V-NET

Metrics	V-net
Dice Coefficient	92
Intersection over Unit	88
Recall	94
F1 Score	96

TABLE. III COMPARISON OF PROPOSED MODEL WITH EXISTING

Model	Accuracy	Precision	Recall	F1 Score
UCF-kinect	85	88	82	85
Ensemble	88	90	86	88
Optimized GRU	92	93	91	92

Table III describes the comparison metrics of the proposed model with existing. In the field of Human Action Recognition employing GRU networks, distinct models are evaluated based on key metrics. The optimized GRU model outperforms both the UCF-kinect model and the ensemble model, achieving an accuracy of 92%. With a precision of 93%, the optimized GRU model demonstrates a higher ability to correctly identify positive examples compared to the other models. The recall rate of 91% suggests that the optimized GRU model captures a higher percentage of true positive cases among all actual positive instances. The F1 Score of 92% indicates a well-balanced performance, with superior accuracy and precision while maintaining a high recall rate.

Fig. 9 illustrates Comparison with GRU. The UCF-kinect model exhibits solid performance with an accuracy of 85%, demonstrating robust overall correctness, while precision at 88% reflects a commendable ability to minimize false positives. However, the optimized GRU model outperforms it, achieving a higher accuracy of 92%, precision of 93%, recall of 91%, and an F1 score of 92%, indicating superior predictive capabilities. The ensemble model, combining multiple approaches, performs even better with an accuracy of 88%, precision of 90%, recall of 86%, and an F1 score of 88%, highlighting the efficacy of ensemble techniques in enhancing overall model performance.

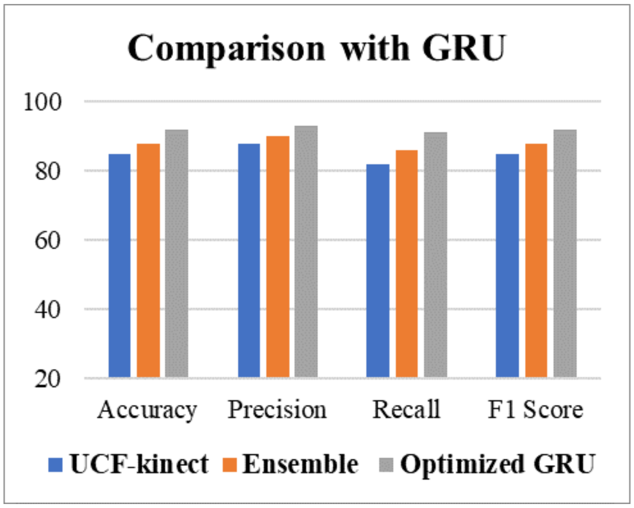

Fig. 9. Comparison with GRU.

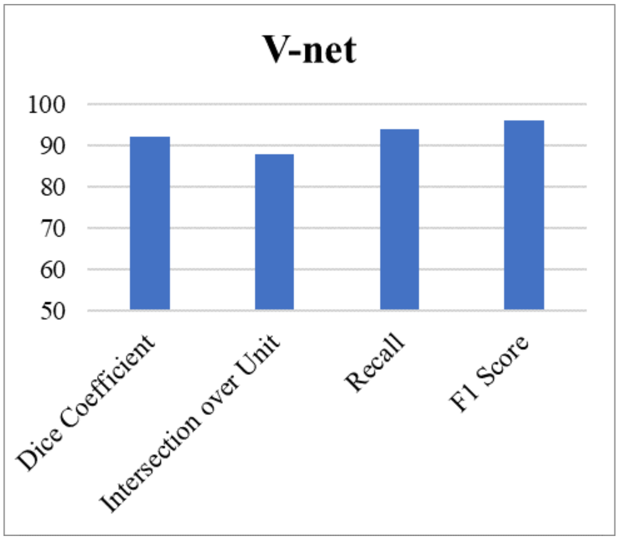

Fig. 10. Metrics of V-net.

Fig. 10 illustrates Metrics of V-net. The V-net model demonstrates strong performance in medical image segmentation, with a Dice Coefficient of 92%, indicating a high degree of overlap between predicted and ground truth segmentations. An Intersection over Union of 88% reflects the effectiveness of the model in capturing the shared area between predicted and true segmentations. Additionally, the model exhibits excellent recall at 94% and a high F1 Score of 96%, emphasizing its proficiency in accurately delineating structures in medical images while maintaining a balance between precision and recall.

Table IV describes the Comparison of Proposed Optimized V-net with Existing. In the comparative analysis of medical image segmentation models, the proposed optimized V-Net stands out with superior performance metrics. The U-Net model demonstrates a Dice Coefficient of 85%, an IoU of 88%, recall of 82%, and an F1 Score of 85%. The IRU-Net model exhibits improvements across these metrics, with values of 88%, 90%, 86%, and 88%, respectively. However, the optimized V-Net outperforms both, achieving a Dice Coefficient of 92%, an IoU of 88%, recall at 94%, and an outstanding F1 Score of 96%. These results emphasize the effectiveness of the proposed optimized V-Net in medical image segmentation, showcasing its ability to produce more accurate and detailed segmentations compared to existing U-Net and IRU-Net models.

TABLE. IV COMPARISON OF PROPOSED OPTIMIZED V-NET WITH EXISTING

Model	Dice	IoU	Recall	F1 Score
U-net	85	88	82	85
IRU-net	88	90	86	88
Optimized V-net	92	88	94	96

Fig. 11 illustrates Comparison with V-net. The U-net model achieves notable results in medical image segmentation with a Dice coefficient of 85%, an IoU of 88%, recall at 82%, and an F1 score of 85%, indicating reliable segmentation performance. The IRU-net model improves upon these metrics, attaining higher scores across the board, with an 88% Dice coefficient, 90% IoU, 86% recall, and an F1 score of 88%. The Optimized V-net, however, outperforms both models with a Dice coefficient of 92%, an IoU of 88%, impressive recall at 94%, and a high F1 score of 96%, showcasing superior segmentation accuracy and robustness.

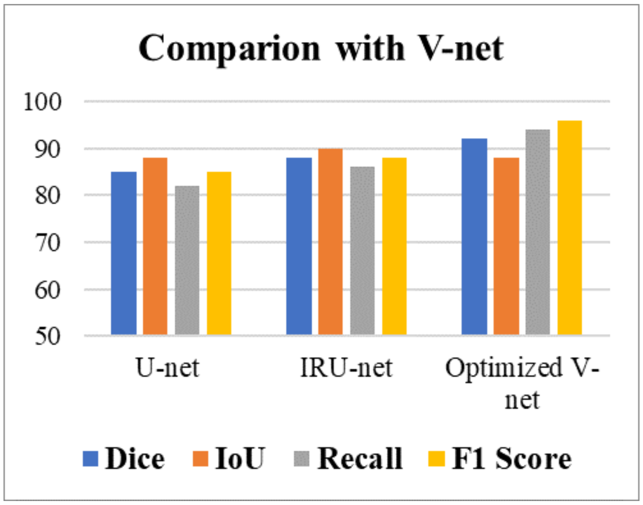

Fig. 11. Comparison with V-net.

C. Discussion

The Python programme created in this work demonstrates strong approaches to min-max normalisation, V-Net-based medical image segmentation, and Adam optimizer-optimized GRU-powered human action identification. With 92% accuracy, 93% precision, 91% recall, and a 92% F1 Score, the GRU-based Human Action Recognition model demonstrates remarkable performance metrics that demonstrate its effectiveness in recognising sequential patterns in video data. With a Dice Coefficient of 92%, Intersection over Union of

88%, 94% recall, and an amazing F1 Score of 96%, the V-Net architecture for Medical Image Segmentation demonstrates its great segmentation skills. These results are astounding. The performance assessment measures for both models, UCF-kinect and Ensemble for HAR, and U-net, IRU-net, and Optimised V-net for medical picture segmentation, are discussed. The optimised GRU and V-Net models outperform their counterparts in terms of accuracy, precision, recall, and F1 score [31] [32]. The training and testing accuracy analysis demonstrates the models' good learning and generalisation, demonstrating their potential for real-world applications in medical imaging and human behaviour detection. Overall, the study demonstrates considerable advances in these areas, giving useful insights for future research and applications.

V. Conclusion and Future Work

The study develops a complete and sophisticated framework for Human Action Recognition (HAR) and Medical Image Segmentation, using Gated Recurrent Units (GRU) networks and the V-Net architecture, respectively. The large gains in accuracy, precision, recall, and F1 Score for both models demonstrate the usefulness of the proposed methods. The inclusion of Min-Max normalisation with the Adam optimizer improves the frameworks' resilience and performance, emphasising the relevance of pre-processing approaches and optimisation algorithms. The study not only provides cutting-edge solutions for HAR and medical picture segmentation, but it also emphasises the general applicability of sophisticated neural network designs and optimisation approaches to complicated problems. Future study approaches might include investigating the use of attention processes in GRU-based HAR to optimise temporal feature emphasis and perhaps improve performance. Overall, this study makes significant contributions to the disciplines of computer vision and medical imaging, opening the path for more complex and accurate applications in real-world situations. Furthermore, future study should look at the use of transfer learning and new loss functions in V-Net-based Medical Image Segmentation to increase generalisation and segmentation accuracy across varied medical imaging datasets.

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Occupancy Measurement in Under-Actuated Zones: YOLO-based Deep Learning Approach

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Abstract—**The challenge of accurately detecting and identifying individuals within under-actuated zones presents a relevant research problem in occupant detection. This study aims to address the challenge of occupant detection in under-actuated zones through the utilization of the You Only Look Once version 8 (YOLO v8) object detection model. The research methodology involves a comprehensive evaluation of YOLO v8's performance across three distinct zones, where its precision, accuracy, and recall capabilities in identifying occupants are rigorously assessed. The outcomes of this performance evaluation, expressed through quantitative metrics, provide compelling evidence of the efficacy of the YOLO v8 model in the context of occupant detection in under-actuated zones. Across these three diverse under-actuated zones, YOLO v8 consistently exhibits remarkable mean Average Precision (mAP) scores, achieving 99.2% in Zone 1, 78.3% in Zone 2, and 96.2% in Zone 3. These mAP scores serve as a testament to the model's precision, indicating its proficiency in accurately localizing and identifying occupants within each zone. Furthermore, YOLO v8 demonstrates impressive efficiency in executing occupant detection tasks. The model boasts rapid processing times, with all three zones being analyzed in a matter of milliseconds. Specifically, YOLO v8 achieves execution times of 0.004 seconds in both Zone 1 and Zone 3, while Zone 2, which entails slightly more computational effort, still maintains an efficient execution time of 0.024 seconds. This efficiency constitutes a pivotal advantage of YOLO v8, as it ensures expeditious and effective occupant detection in the context of under-actuated zones.**

Keywords—YOLO; HVAC system; occupant's position; occupant calculation; under-actuated zone

I. INTRODUCTION

In recent years, increasing attention has been paid to improving the energy security of buildings. The focus has shifted to developing innovative concepts and technologies, increasing the energy efficiency of building envelopes and systems, and optimizing renewable energy sources (RES). Approximately 40% of all structures consume residential or commercial primary energy, and residential or commercial structures consume 40% more energy than others, especially in heating, ventilation, and air conditioning (HVAC) [1]. HVAC is an important system that must be considered, as it significantly. The HVAC system has two zones that must be controlled: under-actuated and fully actuated. The first type, "fully actuated," comprises a single room in which HVAC equipment may be controlled separately [2]. This zone is appropriate for areas with a fixed number of inhabitants and activities such as classrooms, offices, and auditoriums. Meanwhile, under-actuated zones in heating, ventilation, and air conditioning (HVAC) systems are areas where ventilation systems cannot effectively regulate air exchange rates. As a result, these areas can experience substandard air quality, adversely affecting the health [3].

Managing under-actuated zones in buildings presents a complex array of challenges, particularly in controlling the air distribution system. A critical factor in this regard is the direct impact of occupancy numbers on the cooling load [3]. Accurate detection of occupants is therefore essential, as variations in occupancy levels can lead to unbalanced cooling loads [4]. This imbalance often results in inadequate climate control, adversely affecting Indoor Air Quality (IAQ) and diminishing the overall energy efficiency of the system [5]. Further complicating the issue is the limited capacity of ventilation systems in these zones, often characterized by inadequate controls. This limitation can significantly hinder the distribution of fresh air throughout the occupied spaces, exacerbating IAQ issues and potentially impacting occupant health and comfort [6].

Addressing the challenges in under-actuated zones underscores the critical need for precisely adjusting airflow and regulating air temperature based on real-time occupancy data. These dynamic adjustments are essential for maintaining optimal environmental conditions and play a pivotal role in reducing unnecessary energy consumption, particularly in heating or cooling areas that are not occupied [7]. Furthermore, ensuring consistent and high-quality indoor air quality is vitally linked to the well-being and productivity of occupants [8]. In under-actuated zones, where occupancy levels vary and control over environmental conditions is limited, there is an increased risk of periods with compromised air quality [9]. The implementation of advanced occupant detection systems is key to enabling effective HVAC controls [10]. This integration facilitates the processing of real-time occupancy data, empowering the HVAC system to perform predictive adjustments and dynamically tailor its operations to align with the actual occupancy needs. Such an adaptive approach is not only crucial for maintaining comfortable environmental conditions but also has a significant impact on energy consumption [11]. By optimizing HVAC operations based on real-time occupancy data, buildings can realize substantial energy savings [12]. This is achieved by reducing the heating or cooling in less occupied areas, while ensuring that comfort is maintained in areas with higher occupancy [13][14].

Current study has developed occupant detection in such area by utilizing video or image processing. In the context of under-actuated zones, the implementation of video-based occupant detection systems faces unique and formidable challenges, primarily due to the unpredictable and complex nature of occupancy patterns in these areas [15]. Occupants in such zones display a diverse range of behaviors, from moving swiftly through the space to remaining stationary for prolonged durations [16][17][18]. This variability significantly challenges video-based detection systems, which must efficiently track fast-moving individuals and simultaneously accurately count and identify stationary occupants, ensuring comprehensive and precise occupancy detection [19][20]. Compounding this challenge is the intricate physical layout of under-actuated zones, often marked by obstructions and blind spots arising from furniture, partitions, and varied architectural elements [21]. These hindrances substantially reduce the efficiency of camera surveillance, leading to zones where occupants might remain unnoticed. Additionally, another challenge stems from inaccuracies in identifying occupants when utilizing standard video input frame rates. For instance, instances may occur where multiple occupants are present within a zone, yet the identification system detects only a single object. Further investigation into optimizing frame rates is warranted to enhance the accuracy of occupant detection. To address these challenges, camera systems require advanced features and optimized frame rates to accurately count and track occupants across varied scenarios, from low-activity environments to areas with high occupancy and dynamic movement patterns [22]. The unpredictability and diversity of occupant dynamics in under-actuated zones further necessitate the deployment of sophisticated algorithms for data processing and analysis [23]. These algorithms must be capable of interpreting complex and varied data to ensure effective tracking and counting of occupants. This requirement is particularly crucial in under-actuated zones, where environmental conditions may not be as controlled or predictable as those in fully-actuated zones, posing additional.

In this research, we aim to address prevailing gaps by developing a methodology that combines computer vision with deep learning techniques to detect and classify occupants, specifically focusing on quantifying the number of individuals in specific areas within under-actuated zones. Occupant calculation analysis can aid in optimizing indoor air volume distribution in areas with small occupancy HVAC systems. This approach can enhance indoor air quality, minimize energy consumption, and improve occupant comfort and productivity. It is crucial to employ an adept method for analyzing occupant calculation in under-actuated zones. The study centers on implementing the You Only Look Once (YOLO) method, specifically YOLO v8, for detecting occupants in the library rooms of Universitas Trilogi, areas typified as under-actuated zones. A fundamental aspect of this investigation involves analyzing a dataset comprising video input from these under-actuated zones. To facilitate a comprehensive analysis, the dataset was categorized into three types: original, compressed, and slowed down versions. For each frame of video input within these datasets, Roboflow was utilized to annotate the occupants and specific areas of under-actuated zones, thereby creating labeled data essential for training the model. The YOLO v8 model was then employed for each dataset variant, with a focus on investigating the detection confidence threshold to enhance the precision of occupant detection and quantification. A crucial aspect of this study was the comparative analysis of the model's performance, including metrics such as mean average precision, accuracy, and processing time. This performance was benchmarked against state-of-the-art methods like YOLO v5 and Faster R-CNN, providing a comprehensive understanding of YOLO v8's efficacy in occupant detection within under-actuated zone.

II. Related Work

Recent studies have increasingly focused on examining the presence and behavior of occupants in specific zones of HVAC systems, highlighting a keen interest in the correlation between occupancy and system efficiency. Notably, the use of cameras, in tandem with computer vision-based technologies for occupancy detection and recognition, has emerged as a significant area of interest among researchers. This approach is particularly effective as cameras can accurately identify occupants, even those engaged in minimal movement or sedentary activities, a capability crucial for comprehensive monitoring in various scenarios. However, its application in studying and optimizing HVAC systems represents a novel and promising direction in enhancing building energy efficiency.

Tien et al. [8] developed a region-based Faster Convolutional Neural Network (Faster R-CNN) that was capable of detecting and recognizing occupancy patterns and equipment used in an office area. The model was trained and deployed on a regular camera, and field tests were conducted in an office setting. The proposed method was evaluated in the field by recognizing various individuals performing diverse actions in an office environment, such as walking, sitting, and standing. A detection model was created by training a CNN using a transfer learning-based approach to classify occupancy activities. The model was then applied to a camera to enable real-time detection. The model's performance was assessed using a 15-minute experimental detection test, and across all activities, the average detection accuracy was found to be 98.65%.

Wei et al. [24] investigated the potential of using a live occupancy detection approach to help adjust building HVAC system operations to ensure adequate interior thermal conditions and air quality while reducing excessive building energy loads to improve the overall building energy performance. Faster R-CNN models were trained to detect the number of individuals (Model 1) and occupancy activities (Model 2) and deployed to an AI-powered camera to enable live occupancy detection. Model 1 attained an average detection accuracy of around 98.9%, which was higher than Model 2's accuracy of about 88.5%, owing to Model 1's lower complexity. Building energy simulation (BES) model was used to perform scenario-based modeling of the case study building under four ventilation scenarios during the heating and cooling seasons. The results showed that the proposed approach might offer a DCV to improve IAQ and address the under-or overestimation of ventilation demand when utilizing static or fixed profiles. It provides insights into how the proposed approach can adjust HVACs based on occupant dynamic changes and the potential of this strategy to improve indoor air quality and energy efficiency.

Papakis et al. [25] developed a method that can recognize and classify passengers in a vehicle based on cabin photos. The Second Strategic Highway Research Program (SHRP 2) naturalistic dataset containing blurred cabin photos was used to design and test the system. They proposed a CNN-based approach to detect and locate passengers to recognize and identify individuals and classify them as drivers, front-seat passengers, or rear-seat passengers. After assessing various object detection models, to optimize performance, they used the Faster R-CNN architecture with a ResNet-101 backbone, pre-trained on ImageNet, fine-tuned for person detection using SHRP 2 cabin data, and produced the best results. The two distinct test sets found occupant detection accuracies of 94.5% and 98.1%, respectively.

Taheri [11] developed detection-based techniques using the Kanade–Lucas–Tomasi (KLT) tracker to extract many features from video footage. After proposing a conditioning technique for feature trajectories, they introduced a trajectory-set clustering method for identifying the number of moving objects in a scene. Considering these encouraging results, they propose extending our method to identify a more complex model of the appearance and motion of objects. They also plan to investigate the combination of our approach with static object counting methods. Further improvements will include autocalibration (at least to correct the perspective) and background discrimination from objects to ensure the method works for handheld cameras. The result of the proposed method was conducted on three kinds of datasets (USC, Library, and Cells), where the average error of USC was 0.8, LIBRARY was 2.7, and CELLS was 24. This indicates that the proposed method performs well for the USC dataset.

Chatista [15] proposed a novel algorithm for dense-crowd estimation. The proposed method divides an image into small rectangular patches. Each patch underwent a crowd/non-crowd SURF feature binary SVM classifier. These labels and CNN-based head detections were used to estimate the head size in each patch. The count for patches without head detection was estimated using the weighted average of the neighboring pixel counts. This approach was evaluated using three challenging datasets. The results show that our approach yielded low error rates for high- and medium-density crowd images. Because they used a pre-trained head detector trained on totally different data, they aimed to train our head detector on similar high-density crowd images. This would naturally lead to better detection and, thus, better crowd count estimates. Similarly, a perspective-aware head detector would also boost detection accuracy. In addition, better semantic segmentation of the scene for crowd detection is also under consideration. The overlaying of the rectangular grid on the entire image does not consider the image perspective information; the patch size can be modified as the distance from the camera increases to achieve better results. For better results, the SURF classifier can also be trained on less-dense crowd images, especially compared with no weight, with weight having best performance. As shown from the MSE value, SURF classifier with weight has score 61.4 and with no weight has score 79.8.

Previous studies have predominantly utilized the Faster R-CNN method for occupant counting in the realm of computer vision. This method enhances the original R-CNN framework by accelerating performance through shared computation and employing neural networks for region proposal, rather than relying on a selective search [20]. While Faster R-CNN marks an improvement over R-CNN in terms of speed and accuracy, it still falls short in achieving real-time performance, a significant limitation for practical applications [21]. One of the primary reasons for this shortfall is the extensive number of candidate suggestions it generates, approximately 2000, which makes processing time-intensive. For instance, analyzing an image with the bounding box regressor in Faster R-CNN can take around 50 seconds. Moreover, Faster R-CNN is a resource-intensive approach, necessitating substantial storage for feature maps across all regions [23]. This requirement leads to a considerable storage demand, often in the hundreds of gigabytes, due to the need to cache extracted features from the pre-trained CNN on disk for subsequent SVM training [22]. Additionally, being a multi-stage model with distinct components, Faster R-CNN cannot be trained end-to-end, which adds to its complexity and restricts adaptability. Its reliance on selective search algorithms has been critiqued for rigidity and lack of flexibility in diverse scenarios. Most existing research has been focused on enhancing the detection of occupant quantity and distribution in fully-actuated zones. However, there has been a notable gap in developing effective solutions for under-actuated zones, which pose unique challenges due to their variable occupancy and environmental conditions. The need for advanced methods that can effectively address occupant detection in under-actuated zones remains a significant area for further research and development.

III. Materials and Methods

This case study will be conducted at the Universitas Trilogi Library and is shown in Fig. 1. This library consist of five rooms of under-actuated zones includes from number 1 to 5. Each area of under-actuated zones has several distinct areas. The sampling observation and data collection was done in a corner room (room number 4) with three area based ventilation, each of which is 25 m2.

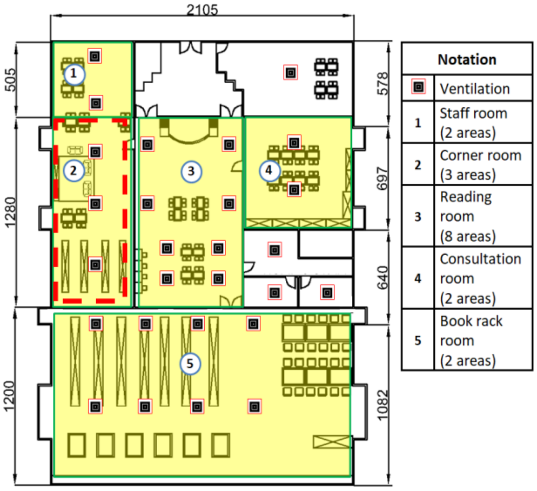


Fig. 1. Layout of Universitas Trilogi Library.

The objective of this research is to determine the arrival patterns of occupants in an under-actuated zone and examine the efficacy of a proposed vision-based, real-time occupancy detection and calculation method. Utilizing YOLO v8, this study aims to accurately identify and count the number of occupants in real-time within such zones. The research methodology is structured into three distinct stages. The first stage, data collection, involves the collection of relevant data variables and their subsequent adjustment to suit the study's needs. The second stage, occupant detection, focuses on identifying and detecting occupants within the under-actuated zone using the YOLO v8 model. The third stage, involves the calculation of the number of occupants present in the zone. The final stage of this research involves a comparative performance analysis between the YOLO v8 model, used for real-time occupant detection in under-actuated zones, and other prevalent models such as YOLO v5 and Fast R-CNN. This comparative analysis aims to evaluate the efficacy, accuracy, and efficiency of YOLO v8 in identifying and counting occupants, in contrast to the performance of YOLO v5 and Fast R-CNN under similar conditions.

A. Data Collection

In our study, we made use of an exclusive dataset that was specifically designed to examine occupancy in under-actuated zones. This dataset was carefully developed through extensive observations that were carried out in three specific areas within the student corner room of Universitas Trilogi library. These areas were identified as under-actuated zones. The data collection process was carried out using three surveillance cameras that were placed in each area in the student corner of the library. The cameras were capable of capturing footage of varying lengths, ranging from 3 to 5 minutes, which resulted in a diverse range of visual data. The footage captured by these cameras provided a detailed and comprehensive view of the occupants and the surrounding environment, such as the tables, chairs, and books. This comprehensive visual data is essential for developing precise 2D object models. The data from each camera offers a unique perspective on the environment, allowing for a multifaceted analysis of occupant behavior and their interaction with the space. The diversity in camera angles and the range of activities captured in the footage ensure a robust dataset.

B. Occupant Detection

This phase involves occupant detection. We utilized YOLO v8 by ultralytics for better throughput with the same number of parameters owing to ultralytics changes, demonstrating hardware-efficient design reforms. All YOLO models were created and used to detect objects. Object detection models were trained to recognize the items in the images. When item classes are discovered, they are surrounded by bounding boxes and are categorized. YOLO is a new algorithm that predicts items and their locations in an image with a single glance. It detects objects in real time using neural networks. This method has evolved over time, beginning with YOLO v1 (or unified), which includes various localization issues and progresses to YOLO v2, YOLO v3, YOLO v4, YOLO v5, YOLO v6, YOLO v7, and YOLO v8(Terven & Cordova-Esparza, 2023).

YOLO divides an image into grids by using a single Convolutional Neural Network (CNN) model. Each grid estimates the bounding boxes and confidence scores. The class of the object in the bounding box is calculated using the predicted confidence score [26]. YOLO v8 variations produce a higher throughput with the same number of parameters, indicating hardware-efficient design reforms. The fact that ultralytics provided YOLO v8 and YOLO v5, with YOLO v5 providing impressive real-time performance, and based on the initial benchmarking results released by ultralytics, it is strongly assumed that YOLO-v8 will focus on constrained edge device deployment at a high inference speed [27].

YOLO v8 is a model that does not rely on anchors. This means that it forecasts the center of an object directly rather than the offset from a known anchor box [27]. Anchor boxes are a very difficult aspect of early YOLO models because they can represent the box distribution of the target benchmark, but not the distribution of the custom dataset. Anchor-free detection minimizes the number of box predictions, which speeds up Non-Maximum Suppression (NMS), a complex post-processing phase that shifts through candidate detection following inference [27]. The first 6 × 6 conv in the stem was replaced with a 3 × 3 conv, the primary building block was modified, and C2f was replaced with C3. The module is depicted below, where "f" represents the number of features, "e" is the expansion rate, and CBS is a block composed of Conv, BatchNorm, and SiLU. C2f concatenates all outputs from the bottleneck (a fancy name for two 3 × 3 convs with residual connections). In C3, only the output of the previous bottleneck was utilized. The bottleneck is the same as that in YOLO v5, but the kernel size of the first convolution increases from 1 × 1 to 3 × 3. Based on this data, we can conclude that YOLO v8 is beginning to regress to the ResNet block described in 2015 [20]. The features were concatenated directly into the neck without forcing the same channel dimensions.

In this study, the YOLO v8 model architecture is utilized for detecting and calculating the number of occupants, a process meticulously illustrated in Fig. 2.

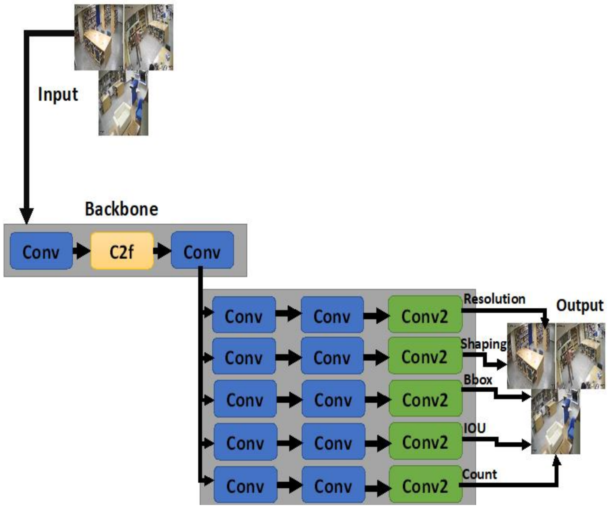


Fig. 2. YOLO v8 model architecture for occupant detection and calculation.

In the sophisticated realm of video-based object detection, the intricately designed model under discussion is specifically engineered to meticulously analyze video input datasets. This analytical journey begins with the critical task of processing raw video footage, a foundational step that determines the efficacy of all subsequent analyses. The core of this model is its head component, which is integral to the complex process of occupant identification within the video stream. The model's head plays a pivotal role in discerning and isolating occupants as distinct entities within the video frames. This task involves a series of intricate steps, beginning with the precise adjustment of the video frames' resolution. This adjustment is not a mere enhancement of visual quality but a strategic decision crucial for balancing clarity with computational efficiency. The model employs advanced algorithms to assess each frame, determining the optimal resolution that ensures clear visibility of occupants while simultaneously minimizing the processing load. This optimization is paramount, as it directly impacts the model's ability to accurately detect and analyze occupants without overburdening the system’s computational resources. Furthermore, the model incorporates sophisticated techniques to handle variations in lighting, movement, and background complexity within the video frames. These techniques include dynamic contrast enhancement for low-light conditions, motion stabilization for dynamic scenes, and background subtraction algorithms to isolate occupants from complex backgrounds. Each of these techniques contributes to the model’s overall efficiency, ensuring that the occupants are detected accurately regardless of the varying environmental conditions within the video footage. In addition to resolution adjustment and environmental adaptation, the model's head also integrates advanced object recognition algorithms. These algorithms leverage deep learning techniques to discern occupant characteristics, differentiating them from other objects in the frame. The model is trained on extensive datasets, enabling it to recognize a wide range of occupant attributes and behaviors, further enhancing its detection accuracy. The processing of raw video footage, therefore, is a multifaceted and complex endeavor within this model.

The intricate process of object detection in video analysis using the YOLO v8 model consists of several carefully orchestrated stages. The first stage is the preprocessing phase, an essential component of the process. This stage is focused on normalizing video quality and resolution, which lays the foundation for optimal detection performance. During this stage, each video frame is thoroughly analyzed and adjusted to ensure that its quality and resolution are suitable for the detection process. It is crucial to maintain a delicate balance between preserving essential details necessary for accurate identification and optimizing the frames to reduce computational load. The preprocessing phase employs techniques such as dynamic resolution scaling and adaptive bitrate control to maintain the integrity of crucial visual information while ensuring that the frames are not excessively data-heavy. Once the preprocessing phase is complete, the YOLO v8 model moves on to the object detection stage. The model's head, a central component in the architecture, plays a crucial role in this stage. The model's head is designed to efficiently distinguish and identify occupants within the video frames as unique entities. This involves deploying advanced neural networks that have been trained on extensive datasets to recognize human figures and differentiate them from other objects in the frame. Bounding boxes are a critical component in this phase. For each detected occupant, the model meticulously generates a bounding box, carefully encapsulating the occupant. This encapsulation is crucial as it isolates the occupant from the surrounding environment and other non-relevant elements within the frame, ensuring that each detection is distinctly recognized. The positioning and sizing of these bounding boxes are calculated with precision, taking into account the contours and dimensions of each occupant. Once the bounding boxes are established, the YOLO v8 model embarks on a probabilistic assessment to ascertain the likelihood that the objects within these boxes are indeed occupants. This assessment involves calculating confidence levels for each detection, a process that draws upon the model's learning from numerous annotated examples. These confidence levels serve as a measure of the model's certainty in its detections. To enhance the accuracy and reliability of the detection process, the model applies a threshold for these confidence levels. Detections that fall below this threshold are deemed less likely to be accurate and are consequently filtered out. This thresholding is a crucial step in ensuring that the occupant count is not only precise but also reliable, as it effectively eliminates false positives and other erroneous detections. In the final stage of the process, the YOLO v8 model performs the occupant counting task. This involves a comprehensive analysis of the detected occupants, considering factors such as the varying sizes, positions, and even the potential occlusions of the occupants within the frames.

Intersection over Union (IOU) is a metric that is widely regarded for its intuitiveness and effectiveness in the field of object detection, particularly in tasks involving bounding box predictions [28]. The computation of IOU involves a straightforward yet insightful mathematical formula. Essentially, it is calculated by taking the area of overlap between the predicted bounding box and the ground truth bounding box (the actual object's location), and then dividing this overlap area by the union area of these two boxes. The union area is the combined area covered by both the predicted bounding box and the ground truth bounding box, minus the overlap area, following in Eq. (1).

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \tag{1}$$

The simplicity of the IOU calculation allows for easy visualization and understanding. One can easily picture the overlapping areas of the two boxes to comprehend how well the predicted bounding box aligns with the actual object’s position and size. This visualization aspect makes IOU a particularly accessible metric for evaluating the accuracy of object detection models.

C. *Occupant Calculation*

In this phase a zone is created by setting the coordinates in the frame. The OpenCV library was used to visualize the zone. A zone was created by setting the coordinates in the zone. Before we can start counting objects in a zone, we must first define the zone in which we want to count objects [29]. The coordinates of the zones are required. We use these later to determine whether an object is inside or outside the zone. To calculate the coordinates inside a zone, we can use Polygon Zone, an interactive web application that allows to draw polygons on an image and export their coordinates for use with supervision. Once we have added points, a NumPy array will be made available on the page. This array contained the coordinates of the points in the zone [30]. The next step was to identify persons in each frame of the movie using a pretrained YOLO v8 object detection model. The number of objects in the zone is calculated by counting the number of objects with unique IDs. Subsequently, a limit was imposed on this zone. We begin by importing the necessary dependencies and then describe the zone in which to count the items using coordinates [27]. Subsequently, we initialized the objects to be used to process and annotate the video. The zone object tracks the zones in our image, and annotators are used to describe how the predictions in our movie should be annotated [27]. We filter out all classes by specifying that we only want detections with class ID 0. This ID maps to the “person” class. This object recognition and tracking system in a specified zone is useful for counting occupants in a zone in the HVAC system area and for creating several zones to track occupants in an under-actuated zone region.

D. Performance Evaluation

Several indicators were utilized to measure the accuracy and efficacy of the suggested method for counting people in a certain region. Typical YOLO performance metrics processing time mean average precision (mAP), and accuracy [31]. mAP is a typical evaluation metric that delivers a single figure as the mean of the Average Precision (AP) values for all classes. This allows for the evaluation of the performance of a model using a single number. As a result, mAP is the most commonly used evaluation metric for object detection algorithms. This is calculated as follows:

$$mAP = \frac{\sum_{q=1}^{Q} AveP(q)}{Q} \tag{2}$$

where, Q is the total number of queries in the set and q is the average precision query. Because our study only has a "person" class, the number of classes will be one. mAP indicates that the confidence threshold (IOU). The Accuracy indicates how close the estimation values of the proposed method are to the true values, and is excellent if it is high. The Accuracy score is calculated by dividing the number of correct predictions by the total prediction number [32]. The accuracy rate formula was calculated as follows. (TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative):

$$Accuracy = \frac{Tp+Tn}{Tp+TN+Fp+Fn} \tag{3}$$

IV. Result and Discussion

A. Result

The dataset was meticulously compiled through observations in the student corner room at Universitas Trilogi, which is divided into three zones. It originated from three video inputs, each three to five minutes long, capturing detail of occupants within the library's student corner. For each of dataset was expanded into three distinct subsets: the original, compressed, and slowdown. The development environment was established using Google Collabs, a platform for Python programming, integrating several libraries including numpy, ultralytic, and supervisory. Notably, YOLO v8, provided by ultralytic, was selected for its enhanced throughput capabilities, maintaining efficiency with the same parameter count due to ultralytic improvements. The model's third segment was dedicated to occupant’s detection and counting.

Tables I, II, and III provide a detailed overview of the datasets used for the training and testing of object detection models across three distinct zones. Each table is specifically allocated to one zone and further categorizes the datasets into three types: Original, Compressed, and Slowdown. These categories are indicative of the different forms of video data utilized in model development. The objective of dividing the three datasets is to evaluate whether the comparison of the number of frames in the dataset has an impact on the result.

The Original Dataset, as represented in these tables, adheres to a standard format. It features a default time duration and maintains a frame rate of 30 frames per second (fps). This dataset serves as a baseline, offering a conventional setting for evaluating model performance. In contrast, the Compressed Dataset focuses on data efficiency. For each zone, the video data is modified by reducing the total frame count to a uniform 500 frames. This approach is designed to test the models in scenarios where full-frame rates are unavailable or computationally burdensome, assessing the models' performance under data-limited conditions. The Slowdown Dataset, on the other hand, is intended to evaluate the models' capabilities in handling more extensive frame sequences. This is achieved by augmenting the total frame count by 30% relative to the original dataset for each zone. Such an increase in frames is aimed at simulating situations where detailed temporal information is crucial for accurate object detection.

TABLE I. DATASET OF ZONE 1

Dataset	Frame	Training	Testing
Original	7045	6340	705
Compressed	285	256	29
Slowdown	8526	7532	994

TABLE II. DATASET OF ZONE 2

Dataset	Frame	Training	Testing
Original	2821	2445	376
Compressed	119	106	13
Slowdown	3647	3283	364

TABLE III. DATASET OF ZONE 3

Dataset	Frame	Training	Testing
Original	2925	2630	291
Compressed	195	175	20
Slowdown	4248	3819	429

For Zone 1, as shown in Table I, the Original dataset comprises 7045 frames, predominantly used for training (6340 frames) with a smaller subset for testing (705 frames). This extensive dataset provides a solid foundation for robust model training. The Compressed dataset, with a total of 285 frames (256 for training and 29 for testing), presents a more condensed form of data, posing potential challenges due to the loss of detail. The slowdown dataset is the most extensive, with 8526 frames, where 7532 are used for training and 994 for testing, offering a vast range of data to assess the model under various temporal conditions. In Zone 2, as per Table II, the dataset sizes are smaller compared to Zone 1. The Original dataset contains 2821 frames, split between 2445 for training and 376 for testing. The Compressed dataset, consisting of 119 frames (106 for training and 13 for testing), is significantly smaller, while the slowdown dataset, the largest in this zone with 3647 frames, is divided into 3283 for training and 364 for testing. This dataset size variation is crucial for evaluating the model's adaptability to different data scales and resolutions. Zone 3, detailed in Table III, mirrors Zone 2 in terms of dataset sizes. The Original dataset has 2925 frames, with 2630 dedicated to training and 291 to testing. The Compressed dataset, comprising 195 frames (175 for training and 20 for testing), and offers a compact data set for model evaluation. The largest dataset in this zone is the slowdown category, with 4248 frames, 3819 for training and 429 for testing, which is instrumental in assessing the model's performance over extended periods. The assessment of the occupant detection model encompassed three distinct areas and four datasets. Tables IV through VI provide essential metrics, including mean Average Precision (mAP), accuracy, recall, and processing time, which are crucial for evaluating the performance of the occupant detection model across four datasets and three zones, utilizing the YOLO v8.

TABLE IV. OCCUPANT DETECTION OF ZONE 1

Dataset	mAP	Accuracy	Recall	Time
Original	99.2	98.4	98.6	0.004
Compressed	92.6	90.6	97	0.004
Slowdown	96.8	96.4	95.5	0.004

In the realm of scientific research, particularly in the evaluation of occupant detection systems within Zone 1 as presented in Table IV, a meticulous comparative analysis between the Original, Compressed, and Slowdown datasets unveils notable differences in their respective performance metrics. This detailed examination is pivotal for assessing the system's accuracy and efficiency under varying data conditions, providing insights into the adaptability and robustness of the detection models. The Original dataset emerges as the benchmark for performance, demonstrating exceptional precision and reliability in occupant detection. It boasts a Mean Average Precision (mAP) of 99.2%, signifying near-perfect accuracy in distinguishing true positives from false positives. Additionally, an accuracy rate of 98.4% and a recall rate of 98.6% underscore the model's effectiveness in correctly identifying true positives and negatives, with minimal instances of false negatives. The rapid execution time of 0.004 seconds further accentuates the model's swift processing capability, a critical factor for real-time applications. In comparison, the compressed dataset, designed to assess performance under data-limited conditions, shows slightly diminished but still robust metrics. It achieves a mAP of 92.6%, indicating strong precision in a compressed frame environment. The accuracy rate stands at 90.6%, and the recall rate at 97%, both of which are commendable given the dataset's reduced frame count. Notably, the model maintains the same execution speed as the Original dataset, evidencing its efficiency in handling fewer data frames without compromising processing speed. The Slowdown dataset, characterized by an increased frame count, displays a competent performance, albeit with slight variations from the Original dataset. It records a mAP of 96.8% and an accuracy of 96.4%, indicating effective detection capabilities, though with a minor decrease in detecting all actual positives, as reflected by a recall rate of 95.5%. Remarkably, the execution time remains consistent at 0.004 seconds, demonstrating that the model's processing efficiency is not adversely affected by the augmented frame count.

TABLE V. OCCUPANT DETECTION OF ZONE 2

Dataset	mAP	Accuracy	Recall	Time
Original	78.3	66.1	84.9	0.024
Compressed	82.9	84.1	80.9	0.004
Slowdown	84.4	80.9	68.2	0.013

In the results section examining occupant detection in Zone 2, as depicted in Table V, an exhaustive analysis of the Original, Compressed, and Slowdown datasets reveals a diverse range of performances in terms of mean Average Precision (mAP), Accuracy, Recall, and execution Time. The Original dataset exhibits a moderate level of detection capability, with an mAP of 78.3%, an Accuracy of 66.1%, and a notably higher Recall of 84.9%. However, its execution time is considerably longer at 0.024 seconds, suggesting a trade-off between accuracy and processing speed. In contrast, the compressed dataset demonstrates enhanced performance with a mAP of 82.9%, a significantly higher Accuracy of 84.1%, and a Recall of 80.9%. Notably, this dataset achieves these metrics while maintaining a much faster execution time of 0.004 seconds, indicating enhanced efficiency in processing compressed data without compromising detection effectiveness. The slowdown dataset presents an interesting profile, registering the highest mAP of 84.4% and an Accuracy of 80.9%, but a lower Recall of 68.2% compared to the other datasets. Its execution time stands at 0.013 seconds, positioning it between the original and compressed datasets in terms of processing speed. Collectively, these results from Zone 2 indicate varying levels of effectiveness in occupant detection across different datasets. While the compressed dataset stands out for its balanced high performance and efficiency, the original dataset, despite its slower processing time, excels in Recall. The slowdown dataset, on the other hand, offers the best mAP but at the cost of a lower Recall rate. This variance in performance across datasets highlights the importance of dataset selection and optimization in occupant detection systems, as each dataset presents its unique strengths and limitations in accurately and efficiently detecting occupants in Zone 2.

TABLE VI. OCCUPANT DETECTION OF ZONE 3

Dataset	mAP	Accuracy	Recall	Time
Original	96.2	90.1	93.7	0.004
Compressed	93.5	91.1	86	0.004
Slowdown	97.4	94.4	97.1	0.004

Table VI displays the results of occupant detection in Zone 3 using three distinct datasets: the original, compressed, and slowdown. The original dataset in Zone 3 sets a high benchmark in terms of performance. It achieves a Mean Average Precision (mAP) of 96.2%, reflecting its high precision in correctly identifying true positive detections. The accuracy rate of 90.1% further illustrates the model's capability in effectively distinguishing between true positives and negatives. Additionally, a recall rate of 93.7% indicates the model's proficiency in identifying the majority of actual positive cases, thus minimizing false negatives. Notably, these metrics are attained with a rapid execution time of 0.004 seconds, underscoring the model's efficiency in processing. In contrast, the compressed dataset, while exhibiting a slightly lower mAP of 93.5%, demonstrates a high accuracy of 91.1%. This suggests that, despite the reduction in data volume, the model retains its effectiveness in accurate detection. However, the recall rate experiences a decline, dropping to 86%. This reduction points to a slight compromise in the model's ability to identify all true positives following data compression. Despite this, the model maintains the same brisk execution time of 0.004 seconds, indicating that the reduction in recall does not significantly impact the overall processing speed of the system. The slowdown dataset, interestingly, outperforms both the original and compressed datasets in Zone 3. It registers the highest mAP of 97.4%, suggesting superior precision in detection. Alongside, it achieves the highest accuracy of 94.4% and the best recall rate of 97.1%, surpassing the other datasets in effectively identifying true positives and minimizing false negatives. Remarkably, these superior metrics are achieved within the same efficient execution timeframe of 0.004 seconds, indicating that the increased frame count in the slowdown dataset enhances performance without compromising on processing speed.

Three zones were measured in pixels using Roboflow polygon zone web tools, which can convert meters to pixels. These tools are adept at converting measurements from meters to pixels, thereby accurately representing the areas of interest in square meters. This precise conversion is essential for the effective application of object detection techniques, where spatial accuracy is paramount. One of the key metrics in object detection is Intersection over Union (IOU), which is critical for evaluating the accuracy of detection models. IOU quantifies the level of overlap between the predicted bounding boxes and the ground truth, essentially measuring the accuracy of the model's predictions. In this context, the IOU threshold is often set at varying levels - 25%, 40%, and 50%. The selection of these thresholds is strategic, as they represent different degrees of alignment between the model's predictions and the actual observed data. Accurate detection is generally considered when at least half of the predicted bounding box aligns with the ground truth, signifying a 50% IOU threshold. This standard is commonly adopted in various object detection tasks, including occupant detection, ensuring that the model's predictions correspond appropriately to real-world instances. The effectiveness of these thresholds and the overall accuracy of the object detection models are comprehensively evaluated across three different zones. Each zone presents a unique scenario with varying occupant numbers: Zone 1 contains 1 occupant, Zone 2 has 13 occupants, and Zone 3 accommodates 10 occupants. Tables VII to IX provide an in-depth comparison of the accuracy of calculating the number of occupants based on the range of IOU thresholds, juxtaposed against actual observations from the three datasets.

In Zone 1, as presented in Table VII, the performance metrics, including mean Average Precision (mAP), Accuracy, Recall, and processing Time, are examined across three datasets: Original, Compressed, and Slowdown. The Original dataset demonstrates exceptional performance, boasting a high mAP of 99.2%, Accuracy of 98.4%, and Recall of 98.6%, all achieved within an impressively rapid execution time of 0.004 seconds. This signifies the model's ability to accurately detect occupants in Zone 1 with both precision and efficiency. The Compressed dataset, while still maintaining good performance, exhibits a slight reduction in mAP (92.6%) and Accuracy (90.6%), although the Recall remains high at 97%. Importantly, the execution time remains consistent at 0.004 seconds, suggesting that data compression does not significantly impact processing speed. The Slowdown dataset stands out in Zone 1, achieving the highest mAP of 96.8%, Accuracy of 96.4%, and Recall of 95.5%, all accomplished within the same efficient execution time of 0.004 seconds. These results underscore the varying efficacies of the occupant detection system across different datasets within Zone 1.

TABLE VII. OCCUPANT CALCULATION OF ZONE 1

Dataset	IOU	Number of Occupants	Accuracy with actual (%)
Original	0,25	1	100
	0,4	1	100
	0,5	1	100
Compressed	0,25	1	100
	0,4	1	100
	0,5	1	100
Slowdown	0,25	1	100
	0,4	1	100
	0,5	1	100

TABLE VIII. OCCUPANT CALCULATION OF ZONE 2

Dataset	IOU	Number of Occupants	Accuracy with actual (%)
Original	0,25	9	69
	0,4	7	53
	0,5	6	61
Compressed	0,25	10	76
	0,4	7	53
	0,5	6	46
Slowdown	0,25	10	76
	0,4	7	53
	0,5	6	46

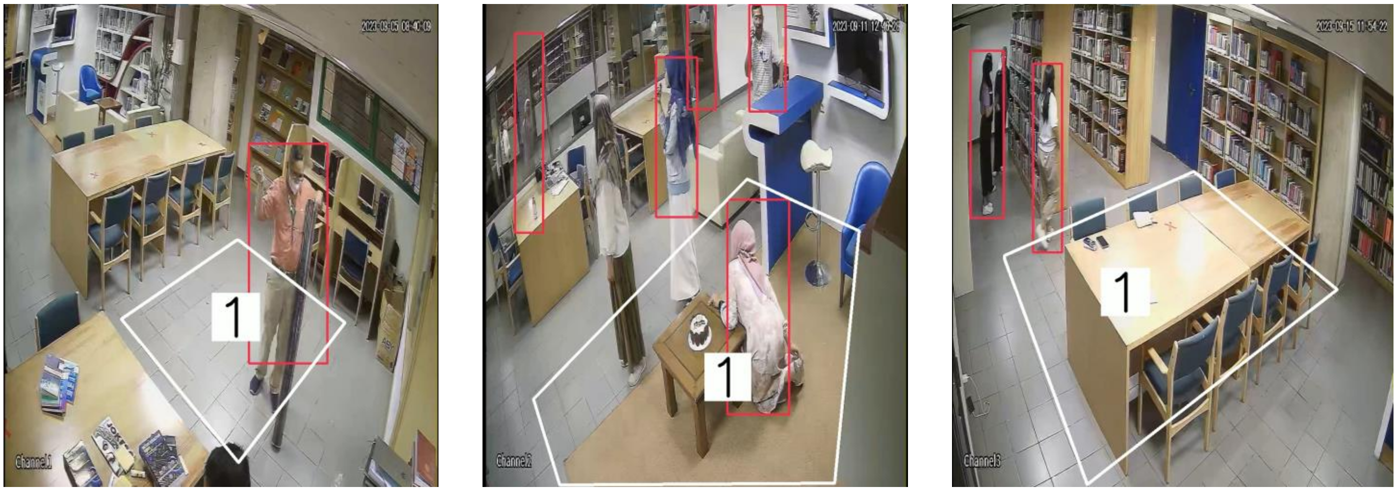
Zone 2, as detailed in Table VIII, presents a similar assessment of performance metrics for Original, Compressed, and Slowdown datasets. In the field of object detection, the analysis of performance metrics across different datasets is essential for understanding the effectiveness of detection models. Table VIII offers such an analysis for Zone 2, comparing the performance of the original, compressed, and slowdown datasets. This comparison is crucial in highlighting how different data conditions affect the metrics such as mean Average Precision (mAP), Accuracy, Recall, and execution Time. The Original dataset in Zone 2 demonstrates respectable performance, characterized by a mAP of 78.3%. This figure indicates a decent level of precision in the detection model's ability to correctly identify true positives. The Accuracy of 66.1% suggests the model's general effectiveness in correctly classifying both true positives and negatives, though it also implies room for improvement. A relatively high Recall of 84.9% is observed, indicating the model's proficiency in identifying a large proportion of actual positive cases. However, this dataset shows a slightly longer execution Time of 0.024 seconds, which, while still efficient, is longer compared to other datasets. In the case of the compressed dataset, a notable improvement in mAP is observed, reaching 82.9%. This increase suggests enhanced precision in occupant detection despite the reduced data volume. The Accuracy also sees a significant rise to 84.1%, demonstrating a considerable improvement in the model's overall detection capability. However, the Recall drops to 80.9%, indicating a slight decrease in the model's ability to identify all true positive cases compared to the Original dataset. Despite these variations in mAP, Accuracy, and Recall, the compressed dataset maintains a rapid execution Time of 0.004 seconds, reflecting efficient processing capability. The Slowdown dataset, designed to test the model's performance with an increased frame count, records the highest mAP of 84.4% among the three datasets. This suggests that the augmented frame count contributes to a more precise detection capability. However, this dataset experiences a drop in Accuracy to 80.9% and a more significant decline in Recall to 68.2%, compared to the compressed dataset. These results indicate a trade-off between the increased precision and the model's ability to accurately classify and identify all positive cases. Overall, the analysis of Zone 2's performance metrics across these three datasets illustrates the inherent trade-offs between various performance measures and the characteristics of each dataset. While the Compressed dataset shows improvements in mAP and Accuracy, it slightly compromises on Recall. On the other hand, the Slowdown dataset excels in precision but at the cost of lower Accuracy and Recall.

In the specialized area of object detection within Zone 3, Table IX presents a critical assessment of the model's performance using three distinct datasets: Original, Compressed, and Slowdown. This comprehensive evaluation is integral to understanding how different data conditions affect key performance metrics such as mean Average Precision (mAP), Accuracy, Recall, and execution time. The Original dataset in Zone 3 sets a high benchmark in model performance. It demonstrates exceptional precision with a mAP of 96.2%, indicating its effectiveness in accurately identifying true positive detections. This is complemented by an Accuracy of 90.1%, reflecting the model's overall reliability in distinguishing true positives from false positives and negatives. Additionally, the Recall of 93.7% is noteworthy, as it signifies the model's ability to detect a large majority of actual positive cases, minimizing the instances of missed detections. All these metrics are achieved within an efficient execution time of 0.004 seconds, highlighting the model's rapid processing capabilities. Conversely, the compressed dataset, designed to assess performance under reduced data volume, maintains a commendable mAP of 93.5% and an even higher Accuracy of 91.1% compared to the Original dataset. This suggests that the model retains its effectiveness and precision in a compressed data environment. However, the Recall experiences a slight decrease, dropping to 86%. This reduction indicates a marginal compromise in the model's capacity to identify all true positive cases in the face of data compression. Despite this, the execution time remains impressively swift at 0.004 seconds, suggesting that the reduction in data volume does not significantly affect the overall processing speed of the system. Remarkably, the Slowdown dataset in Zone 3 outshines the other datasets in terms of performance. It achieves the highest mAP of 97.4%, suggesting superior precision in detection. This is further enhanced by the highest Accuracy of 94.4% and the best Recall of 97.1% among the datasets, indicating the model's heightened capability to accurately classify and detect actual positive cases. The attainment of these superior metrics, interestingly, does not affect the execution time, which remains constant at 0.004 seconds. This underscores the model's ability to handle increased frame counts without compromising processing efficiency.

Collectively, these findings illustrate the varying efficacies of the occupant detection system across different datasets in zone 1, 2, and 3. The original dataset provides a balanced combination of precision and efficiency, while the compressed dataset reveals that data compression slightly impacts recall but with minimal effect on processing speed. The slowdown dataset, with its enhanced frame count, demonstrates potential for superior performance.

TABLE IX. OCCUPANT CALCULATION OF ZONE 3

Dataset	IOU	Number of Occupants	Accuracy with actual (%)
Original	0,25	3	100
	0,4	3	100
	0,5	3	100
Compressed	0,25	3	100
	0,4	3	100
	0,5	3	100
Slowdown	0,25	3	100
	0,4	3	100
	0,5	3	100



a. zone 1 b. zone 2 c. zone 3

Fig. 3. Occupant detection and calculation from original video using YOLO v8.

Fig. 3 provides a visual depiction of the object detection and enumeration process across the three clearly defined zones in Zone 3. It effectively illustrates the system's advanced capability in accurately measuring occupants within designated polygonal regions, corresponding to the zones. The use of the optimal Intersection over Union (IOU) threshold for precise detection is evident in the figure, showcasing the system's proficiency in occupant detection. This visual representation, along with the detailed performance metrics, highlights the varying efficacies and robustness of the occupant detection system across different datasets within zone 1, 2, and 3, demonstrating its adaptability and precision in diverse data conditions. The dataset was used is Slowdown.

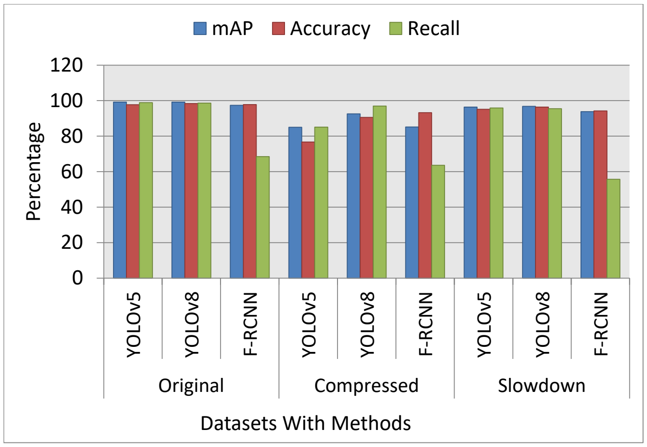


Fig. 4. Performance comparison of zone 1.

Fig. 4 to Fig. 9 offer a comprehensive comparison of the performance metrics for YOLO v8, YOLO v5, and Fast-RCNN across multiple datasets, including the Slowdown Dataset and others utilizing various occupant detection methods. The findings of this research was comparative with Faster-RCNN [8][24][25] and YOLO v5 [21]. The objective is to assess the effectiveness of these models in different detection scenarios. The analysis encompasses several key metrics, such as mean Average Precision (mAP), Accuracy, Recall, and execution Time, which play crucial roles in evaluating the performance of object detection algorithms. These metrics provide nuanced insights into the ability of each model to accurately detect and track occupants across different environments and datasets.

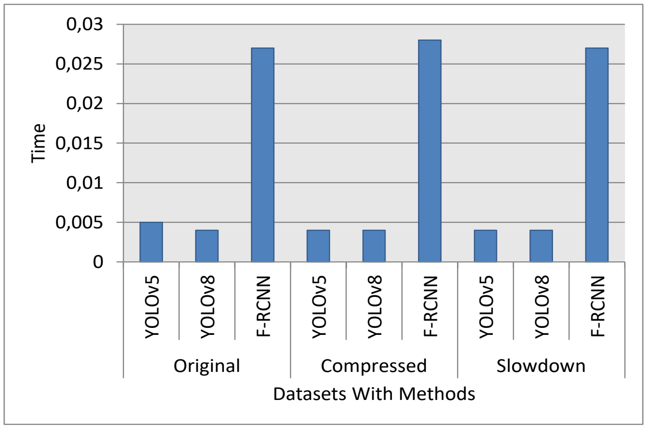


Fig. 5. Time process comparison of zone 1.

In Fig. 4 and Fig. 5, the emphasis is on assessing occupant detection in Zone 1, utilizing three distinct object detection methods. In the original dataset, YOLO v5 and YOLO v8 perform exceptionally well, both achieving a mAP of 99.2%, indicative of highly accurate detection capabilities. YOLO v8 slightly surpasses YOLO v5 in Accuracy, scoring 98.4% against 97.7%, and also demonstrates a marginal edge in processing efficiency (0.004 seconds compared to YOLO v5's 0.005 seconds). However, F-RCNN, despite a decent mAP of 97.4% and Accuracy of 97.8%, shows a significant deficiency in Recall (68.5%), suggesting it misses more true positive detections than its YOLO counterparts. Additionally, F-RCNN's longer processing time (0.027 seconds) may hinder its application in real-time scenarios. The compressed dataset reveals YOLO v8's adaptability, maintaining a high mAP of 92.6% and an Accuracy of 90.6%, with a Recall of 97%. In contrast, YOLO v5 exhibits a drop in performance, with lower mAP (85%) and Accuracy (76.7%), although it still maintains a relatively high Recall of 85.1%. F-RCNN shows some improvement in Accuracy (93.2%), but its mAP (85.2%) and particularly low Recall (63.6%) underscore persistent limitations in comprehensive occupant detection. In the slowdown dataset, both YOLO v5 and YOLO v8 continue to demonstrate strong performance, with mAP values of 96.4% and 96.8% respectively, and Accuracy rates above 95%. Their processing times remain impressively low, underscoring their efficiency in various data conditions. F-RCNN, while showing an improved mAP of 93.8% and Accuracy of 94.2%, continues to struggle with a low Recall rate (55.7%). YOLO v5 and YOLO v8 consistently outperform F-RCNN across different datasets in Zone 1, exhibiting superior mAP, Accuracy, and Recall, coupled with faster processing times.

Fig. 6 and Fig. 7 addresses occupant detection in Zone 2, comparing the same object detection methods across distinct datasets. YOLO v8 achieves the highest mAP of 78.3%, coupled with an Accuracy of 66.1% and Recall of 84.9% in the Original dataset. Compressed data still yields high mAP (84.1%) and Accuracy (82.9%), although Recall is slightly lower at 80.9%. YOLO v5 and F-RCNN exhibit varying performance metrics across datasets, emphasizing the dataset-dependent nature of these methods. In the Slowdown dataset, YOLO v8 maintains its superior mAP and Recall, highlighting its consistent performance.

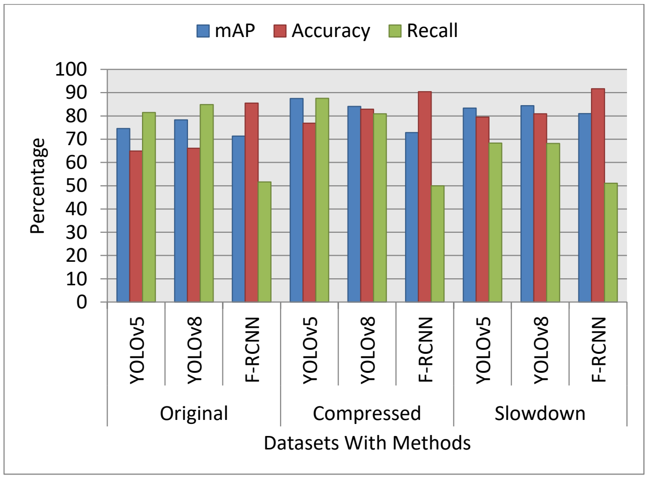


Fig. 6. Performance comparison of zone 2.

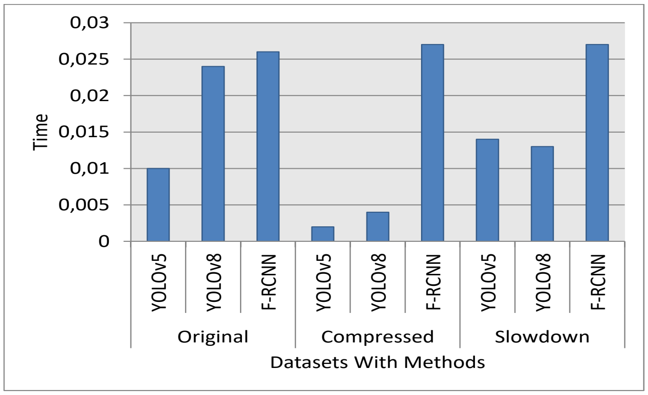


Fig. 7. Time process comparison of zone 2.

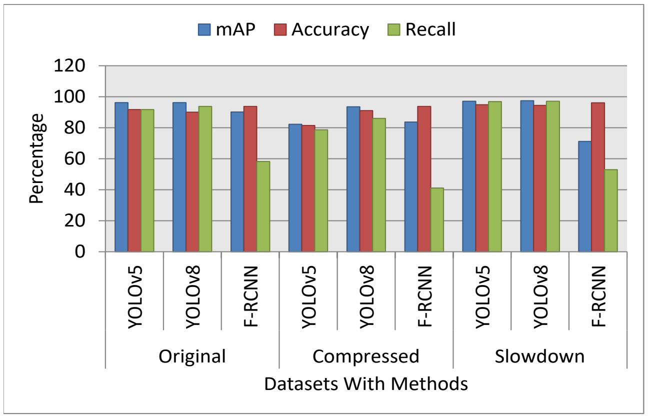


Fig. 8. Performance comparison of zone 3.

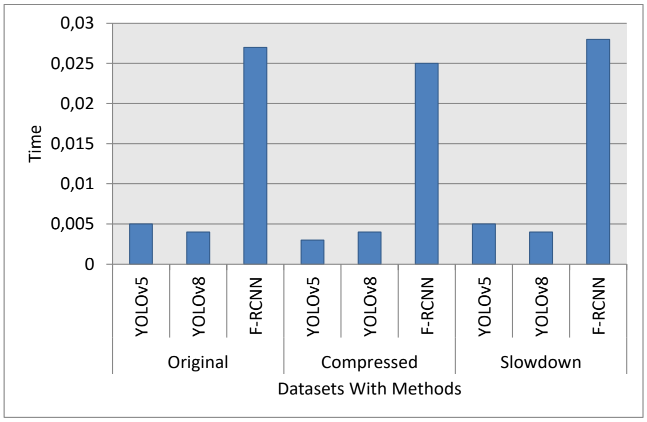


Fig. 9. Time process comparison of zone 3.

Fig. 8 and Fig. 9 focuses on Zone 3, where YOLO v5 and YOLO v8 continue to perform well in the original dataset, both YOLO v5 and YOLO v8 exhibit remarkably consistent and high-performance levels. They each achieve mAP of 96.2%, indicating a highly accurate ability to detect and identify occupants within this zone. Additionally, these methods demonstrate substantial Accuracy and Recall, reflecting their precision and reliability in correctly identifying true positives without missing significant detections. The analysis of the compressed dataset highlights the exceptional adaptability of YOLO v8. It achieves a notable mAP of 93.5%, maintaining high Accuracy and Recall rates despite the challenges posed by data compression. This performance suggests that YOLO v8 is particularly suited for scenarios where data integrity might be compromised or where bandwidth limitations necessitate data compression. In the context of the Slowdown dataset, both YOLO v5 and YOLO v8 continue to excel. They demonstrate robustness in mAP, Accuracy, and Recall, underscoring their effectiveness even under conditions that may affect the speed or flow of data input. Their high performance in this dataset is indicative of their ability to maintain reliability and accuracy in less-than-ideal operational environments. Faster R-CNN, while showing competitive performance in certain scenarios, does not consistently match the overall performance metrics of YOLO v5 and YOLO v8. This observation suggests that while F-RCNN can be effective in specific contexts, it may not be the optimal choice for all scenarios, particularly those represented in Zone 3.

In Zone 1, YOLO v8 achieves an outstanding mAP of 99.2%, indicating its high precision in detecting occupants. The Accuracy of 98.4% showcases its ability to correctly classify occupants, while the Recall of 98.6% demonstrates its capability to capture almost all actual occupants. Furthermore, YOLO v8 maintains a swift execution time of 0.004 seconds, indicating efficiency in processing. In Zone 2, YOLO v8 continues to demonstrate its efficacy with mAP of 78.3%, reflecting its strong performance in detecting occupants. The Accuracy of 66.1% suggests that it correctly classifies occupants in the zone. Moreover, the Recall of 84.9% underscores its ability to capture a significant portion of actual occupants. Despite a slightly longer execution time of 0.024 seconds compared to Zone 1, it remains efficient. Zone 3 further emphasizes the efficacy of YOLO v8, with mAP of 96.2% showcasing its precision in occupant detection. The Accuracy of 90.1% reflects its high classification accuracy, and the Recall of 93.7% indicates its ability to capture the majority of actual occupants. YOLO v8 maintains an efficient execution time of 0.004 seconds in this context. Overall, YOLO v8 demonstrates remarkable efficacy, consistently achieving high mAP values across all three zones, signifying precise occupant detection. Its competitive Accuracy and Recall values further validate its effectiveness. Additionally, its efficient execution times indicate that YOLO v8 combines both efficacy and efficiency, making it a strong candidate for occupant detection tasks in various scenarios.

B. Discussion

The study Occupancy Measurement in Under-Actuated Zones presents significant results in regards to the effectiveness of the YOLO v8 model in accurately detecting and quantifying occupants in difficult environments. The research, which was conducted through the compilation of a comprehensive dataset via video observations in the student corner room at Universitas Trilogi, demonstrates the superior performance of the YOLO v8 model in occupant detection, particularly in dynamic under-actuated zones with varying occupancy patterns and complex environmental conditions. The model's real-time detection capabilities, high accuracy in identifying occupants, and efficient object localization highlight its adaptability and robustness in diverse situations. The study's key findings include the model's ability to precisely identify and count occupants in real-time within the segmented zones of the student corner room, showcasing its spatial accuracy and object localization proficiency. The research's quantitative metrics, including mean Average Precision (mAP), Accuracy, Recall, and execution time, highlight the model's effectiveness in accurately identifying true positive detections while minimizing false positives and negatives. Additionally, the YOLO v8 model's swift execution time further emphasizes its efficiency in data processing and real-time results delivery. Overall, the research findings suggest that the YOLO v8 model has the potential to revolutionize occupant detection systems in under-actuated zones, offering a promising solution for optimizing occupancy monitoring and management in complex environments. The study lays the groundwork for future research and development in the field of object detection and occupancy measurement, specifically focusing on addressing the unique challenges presented by under-actuated zones. The results of this study provide valuable insights into the capabilities of the YOLO v8 model and its potential applications in various industries. The research findings are a significant contribution to the field of occupancy measurement and highlight the potential of the YOLO v8 model as a solution for optimizing occupancy monitoring and management in challenging environments. The study's results also suggest that the YOLO v8 model could be a useful tool for a variety of industries, including but not limited to, security, safety management, and facilities management. The research findings are a valuable resource for academics, researchers, and professionals working in the field of occupancy measurement and object detection.

V. CONCLUSION

This study presents a comprehensive evaluation of occupant detection methods across three distinct zones using YOLO v8. The quantitative analysis demonstrates the efficacy and efficiency of YOLO v8 in occupant detection tasks. In Zone 1, YOLO v8 exhibits exceptional performance with a high mAP of 99.2%, indicating precise detection. The Accuracy of 98.4% and Recall of 98.6% further underscore its effectiveness. Additionally, YOLO v8 maintains an efficient execution time of 0.004 seconds, making it a suitable choice for real-time applications. Zone 2 showcases YOLO v8's efficacy with a respectable mAP of 78.3%, suggesting robust occupant detection. Despite a lower Accuracy of 66.1%, the Recall of 84.9% demonstrates its ability to capture a significant proportion of actual occupants. YOLO v8's execution time of 0.024 seconds in this zone remains efficient. In Zone 3, YOLO v8 continues to perform effectively, achieving mAP of 96.2%, indicating precise detection. The Accuracy of 90.1% and Recall of 93.7% highlight its capability to classify and capture occupants accurately. YOLO v8's efficient execution time of 0.004 seconds makes it a valuable choice for this scenario. The results suggest that YOLO v8 is a robust and efficient method for occupant detection in various zones. Its high precision and competitive recall values make it a promising solution for real-world applications. Future work in this research can explore further optimization of YOLO v8 for occupant detection by considering different datasets and environmental conditions. Additionally, the integration of advanced deep learning techniques and hardware acceleration can enhance both the accuracy and speed of occupant detection systems. Further research can also focus on addressing challenges related to occlusions and multi-object tracking in complex scenarios, advancing the field of occupant detection in smart environments.

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Efficient Simulation of Light Scattering Effects in the Atmosphere

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***Abstract*—Atmospheric light scattering encompasses intricate physical process, including diverse scattering mechanisms and optical parameters. Addressing the challenges posed by the computationally intensive task of deciphering this phenomenon, this study introduces an efficient real-time simulation strategy. The proposed approach employs a physics-driven atmospheric modeling, leveraging a unified phase function to emulate both Rayleigh and Mie scattering phenomena. The scattering integral is approximated and discretized using the concept of ray-marching to solve the scattering integral. Based on the characteristics of different light sources, accurate ray-marching lengths are determined, streamlining the computational trajectory of the light path. Additionally, the introduction of texture dithering enhances the randomness of the initial sampling positions. The Shadow Map algorithm is adeptly employed to generate shadow mapping textures, eliminating the need for light calculations within shadowed regions, thereby reducing the number of samples and computational workload. Finally, color synthesis is used to determine the rendering color of the atmosphere under various fog density conditions. Experimental results show that this approach significantly improves rendering efficiency, and achieves real-time rendering while maintaining a realistic light scattering effect compared with other advanced light scattering rendering methods.**

Keywords*—Light scattering; ray marching; jittered sampling; color synthesis; real-time rendering

I. Introduction

The real-time simulation of atmospheric light scattering is essential for enhancing the realism of virtual scenes [1]. In movies, games, and virtual reality applications, being able to render realistic skies, lighting effects, and weather conditions in real time is crucial for improving users' visual experiences and sense of immersion [2]. Moreover, efficient light scattering simulation also has a significant impact on scientific research in climate change, environmental monitoring, and the field of computer graphics [3].

Currently, the real-time rendering of atmospheric light scattering effects faces two major challenges: one is the high computational complexity, as it requires consideration of the propagation of light through the atmosphere and various parameters such as atmospheric density and scattering coefficients, which involve complex integral calculations; the other is insufficient real-time performance, particularly in large scenes, where even with GPU hardware acceleration, achieving satisfactory computational efficiency and rendering speed remains challenging [4].

In response to the aforementioned issues, we propose an efficient simulation method tailored for the scattering effects of various light sources' rays in the atmosphere. Building upon the physically-based integral solution for light scattering, the method approximates and discretizes the scattering integral, enhancing the ray-stepping algorithm and reducing the length of the computed light paths. Additionally, the Shadow Map algorithm is employed to generate shadow mapping textures, eliminating the need for lighting calculations within shadowed areas, thereby further reducing the number of sampling points. This approach aims to strike a balance between computational efficiency and rendering quality, maintaining realistic simulation effects while enhancing rendering performance to meet the demands of real-time rendering of light scattering. The main contributions of this research are the as follows:

- Enhanced Henyey-Greenstein phase function for Rayleigh and Mie scattering intensities, simplified single-scattering model, and efficient multiple scattering integral computation.
- Optimized Ray-Marching with novel down-sampling method for various light source scenarios, reducing samples while maintaining rendering quality, significantly improving efficiency.
- Enhanced scene realism and 3D effects with optimized ambient and sunlight gradient effects under various times and weather conditions, using scene blending techniques for realistic light scattering.

The paper is structured as follows. Section II reviews previous studies. Section III delves into the construction and optimization of light scattering models, introducing novel techniques and methods. Subsequently, it optimizes the sampling strategy for efficient rendering and presents our approach to atmospheric color synthesis. Section IV presents results and discussions. Finally, this paper concludes in Section V.

II. Related Work

The simulation of light scattering effects relies on the computation of light scattering integrals, which describe the physical phenomenon where light changes its direction of

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propagation due to interactions with particles in a medium. This complex process involves principles of wave optics and variables such as the size, shape, and refractive index of the particles. In the field of computer graphics, light scattering is key to creating realistic lighting effects, particularly when rendering scenes involving fog, smoke, clouds, and other participating media.

To accurately mimic these visual effects, researchers and developers have employed a variety of scattering models that approximate the true scattering behavior. Some widely used theoretical models and methods include: Rayleigh scattering [5], Mie Scattering [6], Henyey-Greenstein Phase Function [7], Monte Carlo Method [8], Light scattering integrals in ray tracing algorithms [9] and so on. Each model and method have its own range of applicability and trade-offs, and the choice often depends on the desired level of accuracy, computational resources, and specific application scenarios.

Currently, optical scattering models in atmospheric scenes are primarily categorized into two main types: empirical models and physical models. Empirical models are typically derived from measurements and statistics of physical parameters such as the shape, size, and concentration of gas particles, in order to deduce the scattering and absorption characteristics of these particles towards light. Empirical models are usually suitable for scenarios with low gas particle concentrations and regular particle shapes. However, physical based models are more applicable for gas environments characterized by complex particle distributions, diverse compositions, or varying properties. Hillaire [10] introduced a novel method for real-time evaluation of multiple light scattering within the atmosphere. By introducing a set of simplified lookup tables and parametrization techniques, it aims to efficiently render skies and their aerial perspectives. This method enables dynamic variations in atmospheric composition to align with artistic visions and weather conditions, eliminating the need for cumbersome LUT updating processes.

To improve the rendering efficiency of atmospheric scattering effects, on the one hand, advancements in computer hardware performance have been leveraged. Modern Graphics Processing Units (GPUs) are utilized for parallel computation and optimized algorithms to accelerate calculation speeds [11]. On the other hand, approaches based on analytical formulae, numerical approximations, and pre-computation are applied to reduce the complexity of integral calculations in atmospheric scattering models, thereby improving computational efficiency. Huo et al. [12] presented an adaptive matrix column sampling and completion method to accelerate the rendering of participating media. However, this method could only handle single scattering scenarios and was not applicable for rendering participating media in dynamic scenes. In 2020, West et al. [13] introduced a novel method called Continuous Multiple Importance Sampling (CMIS) to solve the problem of multiple importance sampling in Monte Carlo integral estimation. This method improves the efficiency of rendering materials, including participating media.

In order to more realistically reproduce light scattering effects, significant progress has also been made in the study of multiple scattering. László et al. [14] improved the traditional light-medium interaction model, allowing control of the extinction coefficient and control variables through approximated sampled values, thereby enhancing rendering efficiency. In 2019, Vibert et al. [15] presented a new scalable hierarchical VRL method that preferentially samples VRLs according to their image contribution, yet this method requires further improvement for rendering anisotropic media. Deng et al. [16] proposed a novel unbiased volume density estimator, the photon surface, which is combined through multiple importance sampling to handle ray paths including single scattering and within-medium transmission. In 2021, Alexander et al. [17] introduced a fitting model for skylight radiance and attenuation in real land atmospheres, significantly enhancing the visual authenticity of existing analytical clear-sky models and the visual realism of interactive methods based on approximate atmospheric light transmission. In the same year, Kettunen et al. [18] proposed a method for improving the efficiency of unbiased volume transmittance estimators. This method reduces variance through various means, resulting in estimators with several orders of magnitude lower variance at the same computational cost, thereby improving the efficiency of ray marching. In 2022, Korkin et al. [19] extended the scope of previous research by considering the reflection of polarized light by a Rayleigh scattering spherical atmospheric layer with highly correlated single-scatter absorption rates. They employed three advanced radiative transfer models to generate numerical results, covering both single scattering and multiple scattering scenarios.

Despite significant advancements in the study of light scattering effects, further exploration is still needed on how to better balance high rendering quality with real-time requirements. In response to the efficiency challenges for rendering atmosphere light scattering, a real-time simulation method for the scattering effects of light in the atmosphere is proposed. This method utilizes approximate numerical calculations and down-sampling to effectively enhance rendering efficiency. Additionally, scene blending techniques are employed to improve the rendering color, resulting in a more realistic portrayal of light scattering effects in the atmosphere.

III. Modeling and Simulation Optimization Methods

A. Constructing Light Scattering Model

Light scattering in the atmosphere mainly occurs through two processes: Rayleigh and Mie scattering. Rayleigh scattering, caused by tiny particles like air molecules, is why the sky looks blue and red during sunrise and sunset. Mie scattering, from larger particles like water droplets and aerosol particles, makes clouds and fog appear white. Our model focuses on these two types of scattering.

The relationship between the intensity of Rayleigh scattering and the wavelength of incident light, as well as the scattering angle, is expressed as shown in Eq. (1):

$$I(\theta) = I_0 \frac{\pi^2 (n^2 - 1)^2 \rho(h)}{2N\lambda^4}(1 + \cos^2\theta) \tag{1}$$

Where $I(\theta)$ is the intensity of scattered light, λ is the wavelength of incident light, θ is the scattering angle, h is the height of the point, I_0 is the intensity of incident light, n is the refractive index of air, N is the density of air molecules at standard atmospheric pressure, $\rho(h)$ represents the relative density of air molecules at height h. When $h{=}0$, then $\rho(h){=}1$. From this, it can be seen that the intensity of Rayleigh scattering is inversely proportional to the fourth power of the wavelength of the incident light. In other words, shorter wavelengths result in stronger scattering. In optics, the phase function is commonly used to describe the scattering properties of light as it interacts with materials. Since Rayleigh scattering is nearly isotropic, meaning that light is scattered uniformly in all directions by particles, its phase function is shown in Eq. (2):

$$F_R(\theta) = \frac{3}{16\pi}(1+\cos^2\theta) \quad . \tag{2}$$

In our model, approximate calculations are performed for Mie scattering, with extinction coefficients and asymmetry factors pre-computed. Combined with the improved Henyey-Greenstein phase function, Rayleigh scattering and Mie scattering can be uniformly described.

In the atmosphere, larger particles interfere with the light collected at the observation point. At this point, the light mapped to the observation point mainly comes from two parts: the light from target reflection attenuated by particles and reaching the observation point, and the atmospheric light formed by light source scattering through particles. Therefore, based on light energy transmission, an atmospheric scattering illumination model is constructed, and the total radiation rate received at point x is shown in Eq. (3):

$$I_c(x,\omega) = I_0(x,\omega)\mathrm{e}^{-\int_0^x \beta_{ex}(x')\mathrm{d}x'} + \int_0^x g(x,\omega)\mathrm{e}^{-\int_{x'}^x \beta_{ex}(x'')\mathrm{d}x''}\mathrm{d}x' \tag{3}$$

Where ω is the incident direction, $I_c(x,\omega)$ is the outgoing light intensity at position *x*, $I_0(x,\omega)$ is the incident light intensity at position *x*, β_{ex} is the extinction coefficient, and $g(x,\omega)$ is the scattering distribution intensity at position *x*. The first part of this equation represents the intensity of light transmitted directly from the light source to the observation point, taking into account the absorption attenuation of light. The second part represents the scattering process through the medium, considering the scattering attenuation of light.

Eq. (4) represents the sum of light intensity scattered from direction ω at point *x*, where the rays from different directions ω_i interact with the medium at that location.

$$g(x,\omega) = \beta_{sc}\int_{4\pi} I(x,\omega_i)F(\omega,\omega_i)\mathrm{d}\omega_i \tag{4}$$

Where $\beta_{sc}{=}\beta\rho$ is the scattering coefficient, β is a tunable parameter, ρ represents the atmospheric density ratio to simulate atmospheric density, $I(x,\omega_i)$ is the incident light intensity from ω_i, and $F(\omega,\omega_i)$ is the phase function of the scattering medium. The angle between ω and ω_i is denoted as θ, which is the scattering angle. Therefore, the phase function can be expressed as $F(\theta)$.

Since this incident intensity is a collection of light emitted from various directions in the sky domain and lacks a specific directionality as a whole, a unified phase function can be applied here. Due to the complexity of the true physical functions for Rayleigh and Mie scattering, using an approximation for the phase function $F(\theta)$ can significantly reduce computational complexity. The directional characteristics of the scattering model vary with particle size. Unlike Rayleigh scattering, the direction of Mie scattering is anisotropic, where light is more scattered forward. Different scattering characteristics can be constructed by combining various linear phase functions and adjusting the values of the asymmetry factor. The Henyey-Greenstein phase approximation function is shown in Eq. (5):

$$F(\theta) = \frac{(1+\cos^2\theta)}{(1+g^2-2g\cos(\theta))^{3/2}} \tag{5}$$

Where g is the asymmetry factor. However, this phase function can only describe forward scattering and cannot accurately simulate the effects of backward scattering. To address this issue, an improved Henyey-Greenstein phase function, as shown in Eq. (6), was adopted to achieve the simulation of backward scattering while avoiding the introduction of excessive complexity coefficients.

$$F(\theta) = \frac{1}{4\pi}\frac{3(1\text{-g}^2)}{2(2+g^2)}\frac{(1+\cos^2\theta)}{(1+g^2-2g\cos(\theta))^{3/2}} \tag{6}$$

The value range of *g* is [-0.75, 0.99]. When *g* is negative, it corresponds to forward scattering, and when g is positive, it corresponds to backward scattering. When the g-value is 0, it results in isotropic scattering, which manifests as Rayleigh scattering.

B. Simplified Integral Solution and Multiple Scattering

During the propagation of light, particles in the air cause scattering of the light. When there are fewer particles in the air, light is usually scattered only once. However, in an atmosphere with a lot of larger particles, the scattered light may continue to be scattered by other particles, resulting in a multiple scattering effect. In conditions where the air quality is poor, multiple scattering can significantly affect our perception of the scene. Computing multiple scattering is complex as it involves extensive integration calculations, making real-time rendering challenging. To address this issue, one can utilize the fact that within a certain area, the variation in particle concentration is typically gradual. Therefore, it's not necessary to calculate the scattered light intensity for every single particle; instead, one can compute the scattered light intensity of some particles along the line of sight to represent the whole.

The specific method, as shown in Fig. 1, involves dividing the air space through which the line of sight passes into several segments, taking the average concentration of like particles within each segment. This allows for segmented sampling based on the variations in atmospheric particle concentration and incident light intensity with distance. The size of each segment needs to be determined by considering the changes in both atmospheric particle concentration and incident light intensity to ensure they remain roughly constant within each segment. The number of segments can be adjusted based on the required drawing precision. This method avoids point-by-point sampling along the line of sight, thereby significantly reducing the computational load.

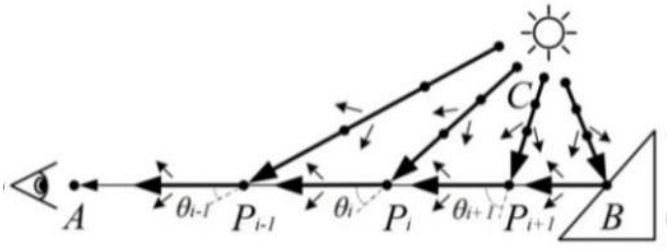


Fig. 1. Schematic diagram of scattered light intensity calculation.

Uniformly select N sampling points along the path AB, denoted as $P_1, P_2 \ldots\ldots P_N$. The total light intensity scattered into the viewer's eye along the line of sight is the sum of particle-scattered light intensities from N sampling segments along the line of sight. After these simplifications, Eq. (3) can be simplified to Eq. (7).

$$I_c = \sum_{i=1}^{N} I_c^i \tag{7}$$

Similarly, when calculating the attenuation coefficient along path CP_i, sampling is also required, with the number of selected points denoted as M. The more sampling points there are, the closer the result is to Eq. (3). However, having too many sampling points can impact real-time performance, necessitating a careful balance. Therefore, Eq. (3) can be discretized into a summation form to significantly simplify the computational complexity, as shown in Eq. (8) and Eq. (9).

$$I_c^{(\upsilon)}(x,\omega) \approx I_0^{(\upsilon)}(x,\omega)\prod_{i=1}^{N} \mathrm{e}^{\beta_{\mathrm{ex}i}^{(\upsilon)}\Delta x} + \sum_{i=1}^{N} g(x,\omega)\prod_{j=i+1}^{N} \mathrm{e}^{\beta_{exj}^{(\upsilon)}\cdot\Delta x} \tag{8}$$

$$g(x,\omega) \approx \sum_{i=1}^{M} I_i^{(\upsilon)} \beta_i^{(\upsilon)} F^{(\upsilon)}(\theta) \tag{9}$$

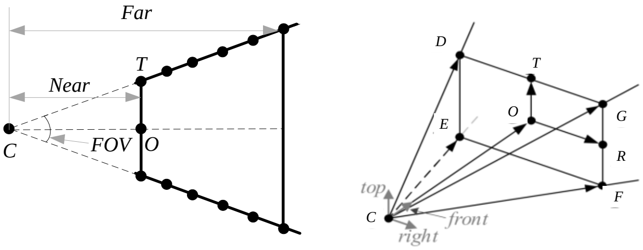
where υ represents the number of multiple computation iterations, N signifies the count of particles with different scattering properties, and M denotes the surrounding voxels that have already been calculated.

Ray-Marching is a ray stepping technique that works by shooting rays from the viewpoint and advancing them step by step, calculating the distance to the surface of objects at each step until a predefined termination condition is met. Its advantages over other methods lie in its ability to achieve extremely smooth effects and handle complex geometries. Rendering performance can be improved by reducing the calculated length of light paths, decreasing the number of samples, and avoiding the computation of unnecessary sample points.

C. Reducing the Length of Ray Marching

When using Ray-Marching for rendering, it's generally assumed to start from the camera position and sample along rays emanating from it until the ray reaches the camera's far clipping plane or intersects with an object. Lighting is a necessary condition for scattering, so it's only necessary to perform ray marching sampling within the range of the lighting. There's no need to march rays throughout the entire scene, which can help reduce the length of the calculated sampling path and improve rendering efficiency. However, different light sources possess varying lighting ranges and other characteristics.

1) Directional Light Ray Marching Path: Rays emitted by directional light sources are mutually parallel, and the illumination can cover the entire scene. Therefore, ray marching needs to take place between the camera's near clipping plane and far clipping plane. The starting point of the ray can be adjusted from the camera's position to its near clipping plane. The position of this new starting point can be determined by the geometric relationship between the camera and the near clipping plane, as shown in Fig. 2.



(a) Directional light ray marching range (b) The relative position of the camera and the near clipping plane

Fig. 2. Schematic diagram for calculating the distance between each point on the near clipping plane and the camera.

In Fig. 2(a), *FOV* represents the opening angle of the visual cone in the vertical direction, *Near* and *Far* respectively indicate the distance from the camera to the near clipping plane and the far clipping plane. In Fig. 2(b), the plane DEFG is the near clipping plane. $\overrightarrow{top}$, $\overrightarrow{right}$ and $\overrightarrow{front}$ represent the camera's upward, rightward, and forward directions. From this, the vectors to the four corner points of the near clipping plane from the camera can be obtained as shown in Eq. (10)-Eq. (13).

$$\overrightarrow{CD} = \overrightarrow{CO} + \overrightarrow{OT} - \overrightarrow{OR} \tag{10}$$

$$\overrightarrow{CE} = \overrightarrow{CO} - \overrightarrow{OT} - \overrightarrow{OR} \tag{11}$$

$$\overrightarrow{CF} = \overrightarrow{CO} - \overrightarrow{OT} + \overrightarrow{OR} \tag{12}$$

$$\overrightarrow{CG}=\overrightarrow{CO}+\overrightarrow{OT}+\overrightarrow{OR} \tag{13}$$

The current camera's aspect ratio is *Aspect*. Based on the positions corresponding to the sampling points in Fig. 4, $\overrightarrow{CO}$, $\overrightarrow{OT}$, and $\overrightarrow{OR}$ can be obtained as shown in Eq. (14)- Eq. (16).

$$\overrightarrow{CO}=\overrightarrow{front}\cdot Near \tag{14}$$

$$\overrightarrow{OT}=\overrightarrow{top}\cdot\left|\overrightarrow{OT}\right|=\overrightarrow{top}\cdot(Near\times\tan\frac{FOV}{2}) \tag{15}$$

$$\begin{aligned}\overrightarrow{OR}&=\overrightarrow{right}\cdot(\left|\overrightarrow{OT}\right|\times Aspect)\\&=\overrightarrow{right}\cdot(Near\times\tan\frac{FOV}{2}\times Aspect)\end{aligned} \tag{16}$$

Substituting Eq. (14)-(16) into Eq. (10)-(13), the computed results are passed to the vertex shader in the form of three-dimensional vectors. The rendering pipeline will automatically interpolate these vectors for each fragment. Subsequently, in the fragment shader, the interpolated vectors can be used to calculate the ray starting point corresponding to each pixel.

2) Point Light Ray Marching Path: Unlike directional light, the illumination range of a point light source is localized and forms a sphere. The actual effective range for ray marching is the intersection between the ray and the lighting sphere. As shown in Fig. 3.

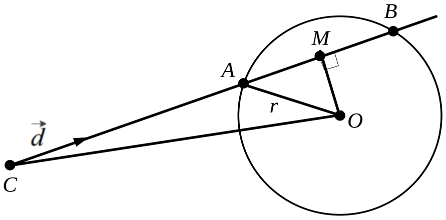


Fig. 3. Analysis of Intersection between light and point light sphere.

The ray emitted from point *C* intersects the sphere with radius *r* and center *O* at points *A* and *B*, where $\vec{d}$ is the unit vector representing the ray direction. According to the definition of vector dot product, the length of the line segment CM is given by Eq. (17), and the square of the length of AM is given by Eq. (18).

$$\left|\overrightarrow{CM}\right|=\vec{d}\cdot\overrightarrow{CO} \tag{17}$$

$$\left|\overrightarrow{AM}\right|^2=r^2-\left|\overrightarrow{OM}\right|^2=r^2-(\left|\overrightarrow{CO}\right|^2-\left|\overrightarrow{CM}\right|^2)\ . \tag{18}$$

According to Formulas (17) and (18), it can be deduced that the intersection point vector between the ray and the point light source's sphere is given by Eq. (19).

$$\begin{cases}\overrightarrow{CA}=\overrightarrow{CM}-\overrightarrow{AM}=(\vec{d}\cdot\overrightarrow{CO}-\sqrt{r^2-(\overline{\overrightarrow{CO}-\vec{d}\cdot\overrightarrow{CO}\cdot\vec{d}})\cdot\overrightarrow{CO}})\cdot\vec{d}\\\overrightarrow{CB}=\overrightarrow{CM}+\overrightarrow{AM}=(\vec{d}\cdot\overrightarrow{CO}+\sqrt{r^2-(\overline{\overrightarrow{CO}-\vec{d}\cdot\overrightarrow{CO}\cdot\vec{d}})\cdot\overrightarrow{CO}})\cdot\vec{d}\end{cases} \tag{19}$$

From this, the starting and ending positions for the ray marching can be determined.

3) Spotlight Ray Marching Path: Similar to point lights, spotlights also have a localized lighting range and exhibit a conical shape, as shown in Fig. 4.

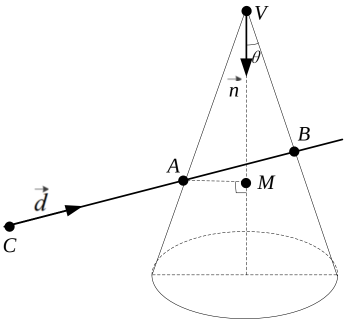


Fig. 4. Analysis of intersection between light and spotlight cone.

The rays emitted from point *C* intersect the cone at points *A* and *B*. Where $\vec{d}$ and $\vec{n}$ are both unit vectors representing the directions of the ray and the axis of the cone, respectively. θ is the angle between the axis of the cone and the generatrix. Therefore, the vector from point *C* to the intersection points between the ray and the cone can be expressed as shown in Eq. (20).

$$\overrightarrow{CA}=t\vec{d} \tag{20}$$

where *t* is the parameter along the ray. Based on the relationships in Fig. 6, Eq. (21) and Eq. (22) can be derived as follows:

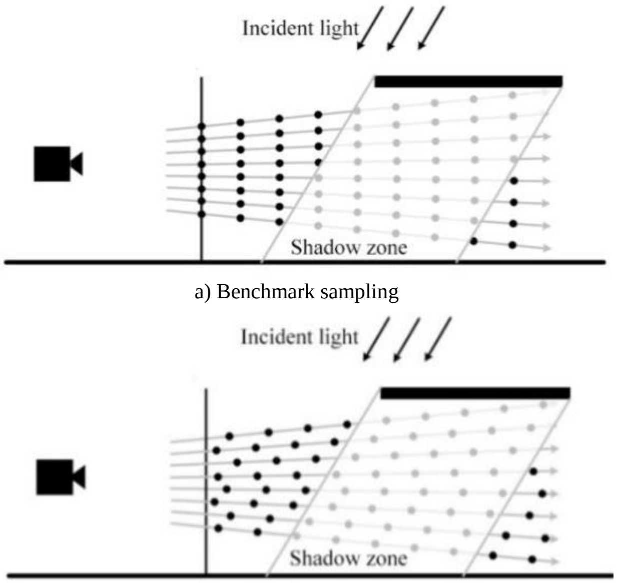
$$\overrightarrow{VA}\cdot\vec{n}=\left|\overrightarrow{VA}\right|\cdot\left|\vec{n}\right|\cdot\cos\theta=\left|\overrightarrow{VA}\right|\cdot\cos\theta \tag{21}$$

$$\overrightarrow{VA}=\overrightarrow{VC}+\overrightarrow{CA} \tag{22}$$

By substituting Eq. (20) and Eq. (22) into Eq. (21) and solving, we can obtain the parameter *t* at which the ray intersects with the lighting cone, thus obtaining the coordinates of intersection point *A*. Similarly, the coordinates of intersection point *B* can be obtained. It's worth noting that due to light attenuation or obstruction by objects, the lighting cone has a certain height limitation. If the height of the lighting cone is set to *h*, it can be determined whether there is an intersection between the ray and the lighting cone by evaluating $0\le\left|\overrightarrow{VA}\right|\cos\theta\times h\le h$.

D. Reducing Sampling Number

During ray marching, increasing the number of sampling can lead to lower simulation efficiency. Therefore, minimizing the number of samples is crucial. However, excessively reducing the sample count may result in noticeable artifacts or banding in the image, significantly affecting realism. This is because larger intervals between sampling points fail to capture sufficient lighting information. From an image processing perspective, this issue belongs to quantization errors and can be mitigated by using dithering. Texture dithering introduces a certain level of randomness in atmospheric light scattering simulations to replicate the complex variability of atmospheric lighting phenomena in the real world. Due to the non-uniform distribution of atmospheric particles in the actual environment, light scattered by these particles creates a natural, seemingly random effect visually. By applying subtle random noise to the image, texture dithering achieves random offsets corresponding to screen pixels, breaking up the regular patterns that quantization errors might otherwise introduce. This method enhances the randomness of sampling points, not only improving the realism of simulated scenes but also optimizing rendering performance without increasing additional computational burden.



a) Benchmark sampling

b) Jittered sampling

Fig. 5. Comparison of benchmark sampling and jitter sampling.

Using the sampling starting positions calculated in Section 4.1 as a reference, Fig. 5(a) depicts the benchmark sampling where the offset is 0. Fig. 5(b) shows the jitter sampling, which adds a random offset on the benchmark starting sampling position, allowing the sampling points between different rays to be staggered. It is worth noting that the random offset should be less than the step size value of the ray marching.

Jittered sampling effectively transforms the color band resulting from reducing the sampling count into noise point in the image. Common methods for generating jitter maps are based on Bayer matrix, white noise, and blue noise. Fig. 6 shows the sampling results under different jitter textures.

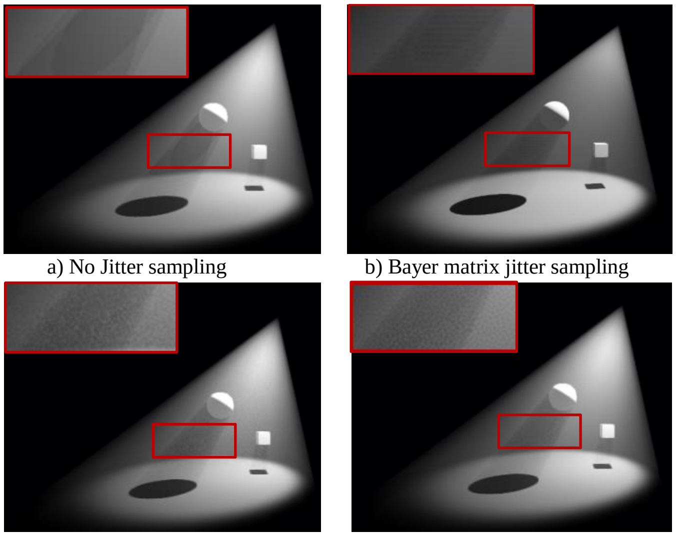
When the sampling count is set to 15, due to the limited number of samples, there will be significant banding distortion at the shadow without using the jitter sampling method, as shown in Fig. 6(a). The jitter texture generated using the Bayer matrix has strong regularity and generates duplicate lattice points, as shown in Fig. 6(b). The white noise jitter texture generates more noise points, resulting in poor performance, as shown in Fig. 6(c). The results generated using blue noise jitter textures exhibit relatively fewer noise points and higher randomness, which is beneficial for subsequent blur processing, as shown in Fig. 6(d). In comparison, the image quality generated by blue noise is better. Therefore, using blue noise to generate jitter textures is recommended. After jitter sampling, the generated noise can be removed using a Gaussian bilateral blur method, while preserving the clear contours of the image. The Gaussian bilateral blur weights of pixels are calculated as shown in Eq. (23).

$$\omega_i(x_i,d_i)=\frac{1}{\sigma\sqrt{2\pi}}\exp(-\frac{x_i^{2}}{2\sigma^{2}}-d_i^{2}) \tag{23}$$

The color contribution value of the *i*-th pixel with a relative distance of x_i and a relative depth of d_i from the target pixel can be obtained by Eq. (23).

Where σ is the standard deviation, and the larger the value, the stronger the blurring effect. These weights need to be normalized before it can be used. The normalized pixel weights are computed as shown in Eq. (24).

$$\varpi_i(x_i,d_i)=\frac{\omega_i(x_i,d_i)}{\sum_{i=1}^{N}\omega_i(x_i,d_i)} \tag{24}$$



a) No Jitter sampling

b) Bayer matrix jitter sampling

c) White noise jitter sampling

d) Blue noise jitter sampling

Fig. 6. Comparison of rendering effects of different jitter textures.

E. *Reduce the Range of Lighting Calculation*

During the process of ray marching, some sampling points might be situated within shadows, as shown in Fig. 5. These sampling points within shadows do not contribute to scattering light. If we can quickly determine whether a sampling point is in shadows, it would help reduce computational workload and enhance simulation efficiency.

Shadow Map is a simple and fast shadow rendering algorithm, which means that when viewed from the position of the light source, all visible objects are illuminated by the light source, and all occluded and invisible objects are in shadow. Firstly, the light source is treated as the camera to render the entire scene and obtain the depth of each object. This depth information is then saved as a texture, which is referred to as the shadow mapping texture. Next, the scene is rendered using the camera's perspective, obtaining vertex coordinates. Transforming these vertices into the light source's coordinate space yields their clipping coordinates (x, y, z) within that space. By utilizing the transformed vertex coordinates (x, y), a sampling of the shadow mapping texture provides the maximum depth value z' for the illumination. If $z< z'$, then the vertex is in the shadow, otherwise it is not in the shadow.

By utilizing the Shadow Map, we can quickly determine whether each sampling point is in shadow. For points within shadows, light intensity calculations can be skipped, as their radiance is considered to be zero since they do not contribute to the final scattered light intensity, effectively reducing the number of sampling points for which light computations are required, thus significantly enhancing rendering efficiency.

F. Improving the Ray Marching Rendering Algorithm

Compared to the traditional Ray-Marching algorithm, the improved Ray-Marching rendering algorithm enhances sampling efficiency, and its pseudo code is shown in Algorithm 4.1.

Algorithm 4.1 Improved Ray Marching Rendering Algorithm:

Input: Pixel information X, Number of ray marching samples N, Light source color Ic

Output: Color corresponding to pixel points

```
Function ImprovedRayMarching(X, N, Ic):
W = CalculateWorldCoordinates(X)
StartPoint = CalculateStartPoint(W)
R = ApplyJitterSampling(StartPoint)
S = GetStepSize(R, N)
I = 0
For i = 1 to N:
        If InShadowRegion(R):
            Continue
        End If
        Ii = CalculateIncidentLightIntensity(R)
        ρ = CalculateFogDensity(R)
        I0 = CalculateScatteredLightIntensity(Ii, ρ)
        I += I0
End For
Pc = Ic * I
Return Pc
End Function
```

When performing atmospheric rendering based on the improved Ray-Marching approach, the initial stage involves recalculating the starting position and step size for ray marching along the direction of rays emitted from the camera. Additionally, jittered sampling is applied along the ray direction. If a ray intersects with an object, its advancement is halted, and distance information is returned. Furthermore, the sampled data and coverage information are utilized to calculate the atmospheric density. Subsequently, the computation of fog area shadows is performed. Rays situated within the shadowed region do not necessitate scattering calculations, and efficiency can be enhanced by excluding these rays. Afterward, atmospheric color values are sampled at the current ray position, and a scene shadow map is generated. This shadow map is then stored in the command buffer for later storage in a texture. Then, it's combined with sunlight and ambient light colors. In addition, lighting calculations are necessary, including extinction coefficient, scattering contribution, and transmittance, among others. After completing these calculations through iterative processes, the final atmospheric color is generated.

G. Atmospheric Color Synthesis

In order to enhance the representation of lighting details, the light scattering effect in fog is simulated using scene blending techniques. Ambient light, as diffused rays, pervades the entire scene and traverses through dynamically changing fog regions. The fog is denser near the ground, resulting in deeper colors. The ambient light generated based on height and time will influence the color of the fog region. Here, a negative cosine function curve is introduced and the time difference range is extended to $[0,\ 2\pi]$. The ambient light color for different heights and times is obtained by multiplying with the ratio of the height field, calculated as shown in Eq. (25).

$$C_{\text{amb}} = \left[\frac{H_{\text{cur}}}{2H_{\text{total}}} \cdot (1-\cos((\frac{T_{\text{cur}}-T_{\text{start}}}{T_{\text{end}}-T_{\text{start}}}) \cdot 2\pi))C_{\text{inc}} + C_{\text{stan}} \right] \tag{25}$$

Where $H_{\text{cur}} / 2H_{\text{total}}$ represents the height field ratio, T_{cur} is the current time, thus the range of $(T_{\text{cur}}-T_{\text{start}})/(T_{\text{end}}-T_{\text{start}})$ is [0, 1], C_{inc} is the incremental color, and C_{stan} is the standard ambient light color. The color and position of sunlight dynamically change with time. Therefore, the corresponding color domain is defined, and the current color value of sunlight is obtained through interpolation based on the time ratio, as shown in Eq. (26).

$$C_{\text{sun}} = [\frac{T_{\text{cur}}-T_{\text{start}}}{T_{\text{end}}-T_{\text{start}}} \cdot C_0 + (1-\frac{T_{\text{cur}}-T_{\text{start}}}{T_{\text{end}}-T_{\text{start}}}) \cdot C_{\text{s-end}}](V_{s\to f} \cdot V_{v\to f}) \tag{26}$$

Where C_0 is the starting value of the sunlight color domain, $C_{\text{s-end}}$ is the ending value of the sunlight color domain, $V_{s\to f}$ represents the vector from the sun to the center of the fog, and $V_{v\to f}$ is the vector from the vertex to the center of the fog.

On the other hand, employing the Alpha blending technique with translucent textures enhances the realism of the fog. To further improve real-time performance, a distance threshold *l* is set to divide the rendering range. Particles within the threshold *l* are only rendered with the particle fog color, while those beyond the threshold *l* exhibit varying lighting effects using UV gradient animation and BillBoard techniques. As shown in Eq. (27):

$$C_{final} = \begin{cases} C_{\text{fog}} & d < l \\ (1-\alpha)\cdot(C_r + C_{\text{sun}} + C_{\text{amb}}) + \alpha\cdot C_{\text{fog}} & d \ge l \end{cases} \tag{27}$$

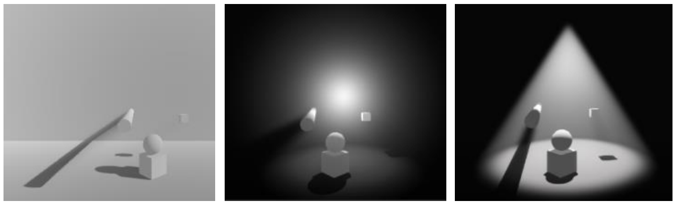
where C_{final} represents the blended rendered color, C_r is the fragment scene color, C_{fog} is the fog color, α is the blending coefficient, which is used to control the degree to which the fog color is influenced by the light.

IV. Discussion and Analysis of Results

To validate the effectiveness of the real-time rendering algorithm for light scattering effects proposed in this paper, simulations of atmospheric light scattering were conducted using Unity. The rendering quality and efficiency of the algorithm were demonstrated, and its performance was evaluated across multiple test scenarios by fine-tuning various algorithmic parameters to assess its robustness in different settings. The experimental environment of the testing platform includes the following hardware components: Intel(R) Core (TM) i7-5820K CPU @3.30 GHz, 16 GB RAM, and the graphics processor is NVIDIA GeForce GTX 1060. The main software used includes OS: Windows 10 (64 bit), development platform: Unity 3D engine, Visual Studio 2017, and the combination of C # scripting language and CG/HLSL shading language to design and render different scenes.

A. Comparison of Scattering Effects under Different Light Sources

The sampling range for ray marching varies under different light sources. Rendering the scene at a resolution of 1280×720 with the same sampling rate, Fig. 7 shows the scattering effects generated under different light sources.



(a) Directional light (b) Point light (c) Spotlight

Fig. 7. Comparison of light scattering effects under different light sources.

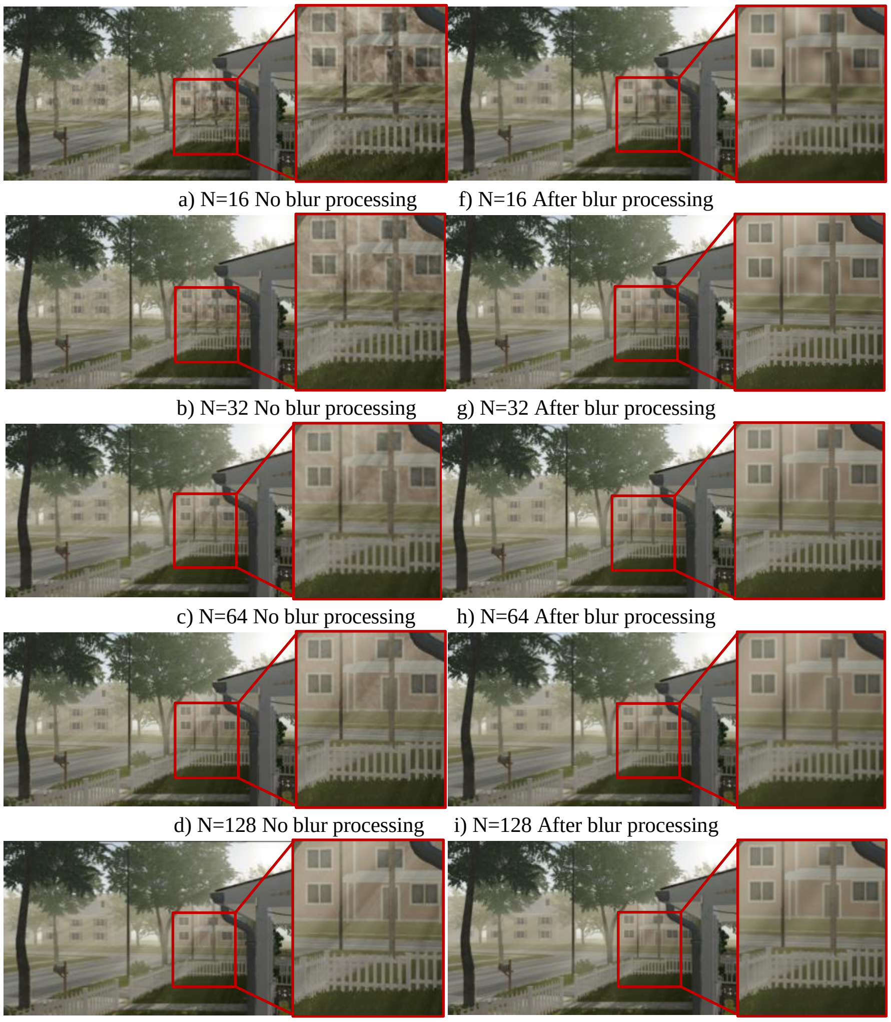
Fig. 7(a) shows a directional light that generates light scattering throughout the entire visual space. When using the traditional ray marching algorithm, the average rendering efficiency is 76.4 FPS. However, with the method proposed in this paper, rendering efficiency has improved to 89.5 FPS, representing a performance increase of 17%. Fig. 7(b) represents a point light source, with its scattering range forming a spherical shape. Fig. 7(c) shows a spotlight, generating a cone-shaped scattering range. Due to their radiation characteristics, point lights and spotlights require more ray sampling to capture variations of light in different directions. Because the scattering range of light in this scene is relatively concentrated, rendering efficiency demonstrates a slight improvement.

B. Comparative Analysis of Rendering Effects with Different Sample Counts

Fig. 8 shows a comparison of volumetric lighting rendering effects in the small town scene with different sample counts (N).

Fig. 8(a)-(e) shows the volumetric lighting rendering effects without Gaussian bilateral blur processing, while Fig. 8(f)-(j) shows the volumetric lighting rendering effects for the corresponding sample counts after the application of blur processing. In 1920×1080 resolution, when the sample count is low, as shown in Fig. 8(a) and 8(b), a lack of sufficient lighting information leads to the presence of numerous artifacts in the scene and the absence of beam effects. Upon applying the blur processing, extensive light spots are formed within the lighting area, as shown in Fig. 8(f) and 8(g). This results in significant distortion of the volumetric lighting rendering effect in the scene. As the number of samples increases, as shown in Fig. 8(c), the lighting area begins to exhibit noticeable beam effects, although some noise points still exist. With further increase in sample counts, more lighting information is gathered, resulting in a more refined and realistic beam effect. When the sample count reaches 256, the generated beam effect becomes quite realistic, as shown in Fig. 8(e). After blur processing, it can be observed that when the sample count reaches 64, the rendered lighting effect appears highly realistic. The beam boundary transition is natural, and the result is very close to the rendering achieved with higher sample counts, as shown in Fig. 8(h)-(j). This implies that, for practical purposes, the rendering effect achieved with a sample count of 64, enhanced by the blur process, can effectively substitute for higher sample counts. The rendering frame rates for different sample counts are shown in Table I. Increasing the sample count enhances rendering quality, but it also raises computational costs. In this complex scene, the rendering efficiency with 64 samples and blur processing can reach 46.4 FPS, which is 82% higher than the rendering efficiency without blur processing with 256 samples.

Therefore, our approach is able to achieve a more efficient and artifact-free realistic atmospheric lighting effect with fewer samples, achieving a balance between the desired visual quality and performance.



a) N=16 No blur processing f) N=16 After blur processing

b) N=32 No blur processing g) N=32 After blur processing

c) N=64 No blur processing h) N=64 After blur processing

d) N=128 No blur processing i) N=128 After blur processing

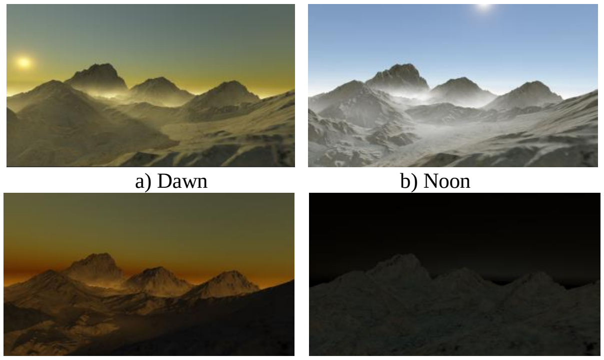
e) N=256 No blur processing j) N=256 After blur processing

Fig. 8. Comparison of volume light rendering effects with different sample counts.

C. Time-Varying Ray Scattering Effect

Fig. 9 shows the comparison of light scattering effects in non-uniform media that dynamically vary with the position of the sun.

Fig. 9(a) and (c) respectively show the light scattering effect under dynamic mountain fog in the morning and after sunset. At these times, the sun is near the horizon, and the sunlight enters the atmosphere at an oblique angle. This leads to significant scattering of blue light along the transmission path, preventing it from reaching the camera. As a result, the closer to the ground, the sky appears orange- yellow or orange-red. Fig. 9(b) shows the scene at noon, where the sky displays a gradient blue due to Rayleigh scattering. However, a noticeable mist-like effect is observed near the ground due to Mie scattering, significantly enhancing the realism of the entire scene. Fig. 9(d) shows the scene at midnight, without considering the influence of light from other celestial bodies, presenting a completely dark effect.



a) Dawn b) Noon

c) After sunset d) Midnight

Fig. 9. Comparison of time-varying light scattering effects in non-uniform media.

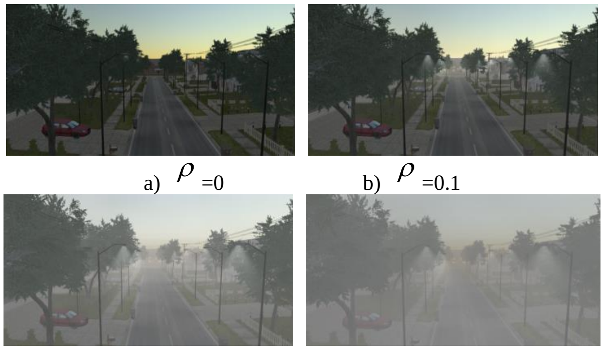
This indicates that the proposed method can effectively present dynamic light scattering effects caused by varying solar positions, enhancing the realism of the rendered scenes. Moreover, it can maintain a rendering efficiency of over 45FPS, meeting real-time requirements.

D. Rendering Effects for Different Atmospheric Density Ratios

The concentration of aerosol particles significantly affects the propagation, color, and intensity of light. Due to the fact that most air pollutants belong to aerosol particles, the intensity of Mie scattering can be affected by adjusting the atmospheric density ratio, thereby simulating the light scattering effect under different air qualities.

Fig. 10(a) presents the lighting scene of an urban street in the early morning, where the atmosphere does not contain aerosol particles. As a result, only the Raleigh scattering effect is evident in the distant sky, and there is no Mie scattering effect near the ground. The light from street lamps is primarily concentrated near the light sources, and there is no noticeable scattering effect. In Fig. 10(b), ρ=0.1, the lighting scene under good air quality is shown. In this case, the Mie scattering effect is evident near the ground. Fig. 10(c) and Fig. 10(d) respectively show the light scattering effects for conditions with ρ=0.3 and ρ=0.5. In both cases, the entire scene is covered by fog, with street lamps forming light beams within the fog.

As the atmospheric density ratio increases, the light scattering effects gradually enhances. The clarity and visibility of objects in the scene significantly diminish, and the sky gradually appears gray blue, in complete accordance with the physical principles of light scattering. This notably enhances the scene's depth and layering, and effectively elevating the realism of light scattering simulation under various levels of atmospheric pollution.



a) ρ =0 b) ρ =0.1

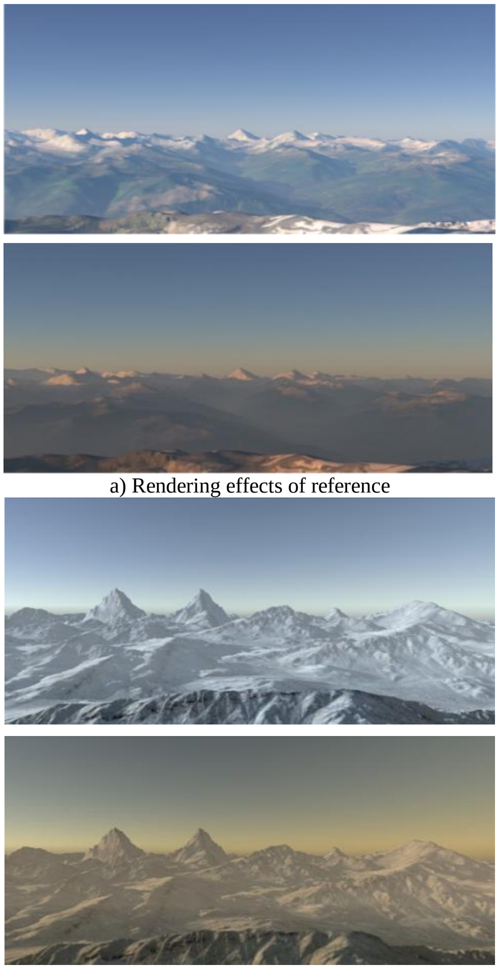
c) ρ =0.3 d) ρ =0.5

Fig. 10. Comparison of light scattering effects under different atmospheric density ratios.

E. Experimental Comparison and Results

Fig. 11 shows the comparison of light scattering effects between this paper and reference [17] in mountain scenes under clear skies.

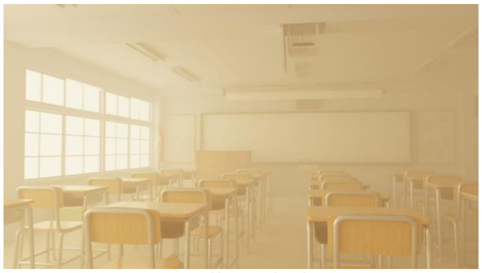
Fig. 11(a) illustrates the rendering results achieved by the method used in literature [17], which is based on an extensive atmospheric scattering dataset. This technique employs data fitting to reduce the size of the dataset and attain high-quality rendering effects. Despite its ability to produce images with a high degree of realism, the method's substantial demand for computational resources and storage space limits its applicability in real-time rendering scenarios. In contrast, Fig. 11(b) presents the light scattering effects realized in large-scale scenes using the method proposed in this paper. By adopting the same solar elevation angle as in literature [17], with the top image set at 15 degrees and the bottom image at 2 degrees, our method achieves visually realistic results comparable to those in literature [17]. Meanwhile, the average rendering frame rate of our method reached 43.6 FPS, fulfilling the requirements for real-time performance. The Mie scattering effect is not obvious in the near area, while it becomes more evident in the far area. This results in clear visibility of objects in the foreground and a gradual blurring and fading of objects in the distance, in accordance with the natural physics of light. Furthermore, as the elevation increases, the Mie scattering effect gradually weakens. And after reaching a certain height, it can still maintain a clear sky color, effectively achieving a realistic light scattering effect under a clear sky. It is worth noting that the frame rate of this method can reach 43.6 FPS, fully meeting the requirements of real-time rendering. In conclusion, our approach significantly improves rendering efficiency while maintaining light scattering effects comparable to those in reference [17]. This not only meets the requirements for real-time rendering but also satisfies the demands of applications with high real-time performance requirements.



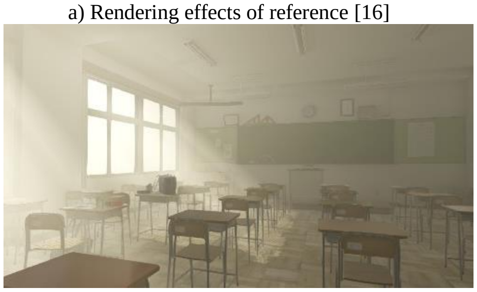
a) Rendering effects of reference

b) Rendering effect of this paper

Fig. 11. Comparison of light scattering effects in mountain scenes between this paper and reference [17].



a) Rendering effects of reference [16]



b) Rendering effect of this paper

Fig. 12. Comparison of indoor lighting scattering effects between this paper and reference [16].

The above experiments were all conducted in outdoor scenes, and our approach is equally applicable to indoor environments. Fig. 12 provides a comparative display of the light scattering effects in a classroom scene between our approach and the method proposed in reference [16].

Fig. 12(a) illustrates the rendering of a scene using the photon surface density estimation method from literature [16], which is suitable for handling cases with highly anisotropic phase functions. However, it fails to meet the requirements for real-time rendering. In contrast, Fig. 12(b) displays the rendering results obtained using the method proposed in this paper, achieving a frame rate as high as 76 FPS, meeting the standards for real-time performance. Moreover, the distribution of light and shadow in our method is similar to that in literature [16], presenting a trend of gradually diminishing brightness from the window to the interior of the room. Our method also achieves the effect of sunlight passing through glass windows, producing noticeable volumetric light beams. This greatly enhances the realism of the scene.

F. Performance Analysis

Table I lists the relevant data for each experimental scenario in this paper. The experimental data indicates that the method proposed in this paper can achieve real-time rendering frame rates in various experimental scenarios, with the sampling numbers not exceeding 256. Particularly, in smaller-scale scenes, higher rendering frame rates can be achieved. Compared to the methods in references [16], our approach has significant advantages in real-time rendering performance while maintaining consistent rendering quality.

TABLE I. EXPERIMENTAL DATA OF DIFFERENT EXPERIMENTAL SCENARIOS

Scenes	Sample Count	Atmospheric Density Ratio ρ	Scattering Coefficient	Resolution	Average Rendering Frame Rate (FPS)
Fig.7 a)	64	0.1	0.33	1280×720	89.5
Fig.7 b)	64	0.1	0.33	1280×720	96.5
Fig.7 c)	64	0.1	0.33	1280×720	98.6
Fig.8 a) (No blur)	16	0.1	0.29	1920×1080	54.2
Fig.8 c) ((No blur))	64	0.1	0.29	1920×1080	48.2
Fig.8 e) ((No blur))	256	0.1	0.29	1920×1080	25.5
Fig.8 f)	16	0.1	0.29	1920×1080	52.6
Fig.8 h)	64	0.1	0.29	1920×1080	46.4
Fig.8 j)	256	0.1	0.29	1920×1080	24.3
Fig.9	64	0.1	0.33	1920×1080	45.8
Fig.10	64	0, 0.1, 0.3, 0.5	0.33	1920×1080	46.2
Fig.11 a) (Reference [17])	-	-	-	1500×1000	<0.003
Fig.11 b)	64	0.1	0.33	1920×1080	43.6
Fig.12 a) (Reference [16])	-	-	-	-	<30
Fig.12 b)	128	0.3	0.65	1280×720	76

V. CONCLUSION

In this paper, a real-time simulation method is proposed for light scattering effects in the atmosphere. By utilizing a physically-based atmospheric model that incorporates both Rayleigh and Mie scattering mechanisms, the total radiance equation is simplified and discretized, to construct a multiple scattering model. In addition, based on different light source characteristics, the method employs accurate ray marching path lengths, jittered sampling, and exclusion of shadowed region samples for lighting computations. This significantly reduces the required number of samples, resulting in a noteworthy enhancement in rendering efficiency, while maintaining stable rendering quality. Rendering is accomplished by utilizing an improved ray marching algorithm to achieve a more accurate simulation of scattering effects. In terms of simulating ambient light and sunlight, this paper optimized the gradient effects under different time and weather conditions. It blends the fog color with scene fragments during rendering, accurately presenting the various scattering properties of light in the atmosphere. In summary, the proposed method has demonstrated excellent performance in both real-time processing and realism, achieving a good balance between computational efficiency and visual effects. It provides valuable reference for further research and applications in the field of light scattering simulation, effectively enhancing the realism and three-dimensional sense of the scene while meeting real-time requirements.

Although our method can achieve real-time rendering in most scenarios, rendering efficiency can still be significantly impacted in cases involving large-scale scenes or high sampling counts. Future research could explore more efficient computational optimization methods to reduce the computational overhead. Meanwhile, the application of blur effects might result in some loss of detail. Efforts can be directed towards finding improved methods that allow for preserving the intricate details of simulation results to their maximum while still maintaining real-time rendering.

ACKNOWLEDGMENT

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Semantic Information Classification of IoT Perception Data Based on Density Peak Fast Search Clustering Algorithm

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***Abstract*—In the rapidly developing field of the Internet of Things today, effective processing and analysis of perceptual data has become crucial. The perception data of the Internet of Things is usually large, diverse, and presents high-dimensional characteristics, which poses new challenges to data clustering algorithms. This study utilizes the K-center point algorithm to optimize the density peak fast search clustering algorithm, proposes a new clustering algorithm, and applies it to the research of semantic classification of perception data in the Internet of Things. Firstly, the K-center algorithm was used to optimize the clustering center optimization process of the density peak fast search clustering algorithm. Then, the optimized algorithm was applied to the automatic semantic classification model. Thus, a new automatic semantic annotation model for IoT aware data has been established. The research results showed that the classification accuracy of the proposed optimization algorithm was as high as 0.98, and the running stability of the automatic semantic annotation model optimized using this algorithm was as high as 0.99, with a running time as low as 1s. In summary, the automatic semantic annotation model built in this study can effectively improve the efficiency and accuracy of semantic classification, thereby providing more accurate and efficient data support for intelligent services.**

Keywords*—*Clustering algorithm; Internet of Things; perceived data; classification; peak density; semantic information

I. Introduction

With the rapid development of the Internet of Things (IoT) technology, more and more devices are connected to the Internet, generating a large amount of sensory data. These data are not only large and diverse in volume, but also exhibit high-dimensional characteristics, bringing unprecedented challenges to effective information processing and analysis [1-2]. Especially in intelligent service domains such as smart city, smart home, health monitoring, etc., how to accurately and efficiently extract valuable semantic information from massive perceptual data has become an urgent problem to be solved [3]. Clustering by Fast Search and Find of Density Peaks (CFSFDP) algorithm has gained wide attention in the field of data science due to its superior performance, especially in identifying the cluster centers, which shows significant advantages. However, CFSDP algorithms still face problems such as inconsistent sample density and sensitivity to noisy data when dealing with IoT sensory data [4]. In addition, the K-center algorithm has better robustness in data classification, but its performance is limited by the choice of centroids [5]. However, existing research mainly focuses on data acquisition and transmission optimization, with insufficient exploration of efficient data processing and accurate semantic classification, failing to give full play to the potential of IoT data in intelligent applications. This study intends to fill this research gap by proposing a Fusion Clustering Algorithm Based on K-Centroids and Fast Search of Density Peaks (FCA-KCFSDP) based on the optimization of K-centroid algorithm, which aims to improve the accuracy and efficiency of semantic information classification of IoT sensory data. This algorithm not only improves the stability and operational efficiency of the classification model by optimizing the clustering center searching process of the clustering algorithm, but also provides a strong technical support for achieving more accurate and personalized intelligent services. The contribution of this study is to clearly point out the shortcomings of the existing research and to achieve excellent performance in semantic information classification of IoT sensory data by proposing and validating a new clustering algorithm. The algorithm outperforms the existing clustering algorithms in terms of classification accuracy, operation stability, and operation time, which provides a new solution for the processing of IoT sensory data, as well as new ideas and methods for subsequent related research.

II. Related Work

CFSFDP is a density based clustering method aimed at addressing some of the limitations of traditional clustering algorithms when dealing with complex datasets. Many experts have conducted a series of studies using this clustering algorithm. In industrial applications, ensuring the reliability of rolling bearing rotating machinery is crucial. Wu J et al. proposed a new bearing fault diagnosis method that extracts bearing features through improved complete set empirical mode decomposition and uses CFSFDP for fault identification. This method was superior to traditional methods in fault diagnosis [6]. Chunhao Z et al. proposed an improved RNN-CFSFDP algorithm to address the limitations of the CFSFDP algorithm. This new algorithm redefined the sample density metric by introducing inverse nearest neighbors, enhancing the robustness of the allocation process, effectively reducing the domino effect, and avoiding incorrect selection of density peaks as clustering centers. The clustering performance of RNN-CFSFDP on manifold and non-uniform density datasets was superior to or equivalent to traditional methods [7]. To ensure vehicle driving safety, Wang H et al. studied vehicle stability identification and coordinated control. Firstly, a vehicle dynamics model was established using the vehicle simulation software Carsim, and an attribute dataset representing the lateral stability of the vehicle was obtained. Subsequently, the CFSFDP algorithm was applied to classify lateral stability. The final simulation results validated the advantages of the proposed method and coordinated control strategy [8]. Ren W et al. proposed an improved algorithm to address the limitations of the original CFSFDP algorithm in anomaly detection. This algorithm effectively reduced storage and computing costs by using a small number of key data points and reducing redundant data, while maintaining the arbitrary shape clustering characteristics of CFSFDP. Compared with traditional clustering algorithms, the improved CFSFDP algorithm performed better in generating anomaly detection files in terms of speed and accuracy, achieving a balance between detection accuracy and real-time performance [9].

The Semantic Information Classification (SIC) refers to the process of classifying text or data based on the semantic information it contains. Currently, many experts have used various algorithms to build various SIC models. Borges J B et al. proposed an IoT time series classification strategy and named it TSCLAS. TSCLAS is a time series classification strategy for IoT data, which mainly distinguishes different categories by transforming the original data into the ordinal pattern domain. At the same time, this strategy also enhanced the dynamic class separability of time series by selecting the optimal parameters. TSCLAS performed well in processing large-scale and incomplete IoT data, and had advantages in classification accuracy and computational time compared to other classification algorithms [10]. Wang Z et al. proposed a novel network structure for multi label image classification, which is a semantic supplementary network with prior information. This network first generated prior information through prior information networks with different convolutional layers, and then used semantic supplementation modules to generate semantic information of potential labels highly related to the current information based on the prior information. The proposed architecture achieved better classification performance in predicting certain semantic related labels [11]. Chen L et al. proposed a method for inferring regional level metadata from building automation system data to address the issue of inconsistent and incomplete metadata in existing building automation systems. Even in the absence of intuitive labels, the proposed information classification method could accurately classify and associate regional level building automation system points. The average accuracy of its classification and association stages was 90% and 85%, respectively [12]. Liu Z et al. proposed a global semantic memory network for aspect level emotion classification tasks. Traditional attention neural networks usually only consider the interaction between aspects in a single sentence and its context when solving this task, ignoring the rich semantic information available in other sentences. This network innovatively treated contexts with similar meanings as global semantic information and incorporated them as domain knowledge into the model to generate domain specific labels, proving its effectiveness [13].

In summary, many current studies have covered the application of CFSFDP and its variants in multiple fields. These studies indicate that the CFSFDP algorithm and its improved versions have advantages in processing high-dimensional, complex, and non-uniform density datasets, effectively identifying key information, and achieving efficient SIC in multiple application fields. However, these methods still have certain limitations in the processing of the IoT sensing data (IoT-SD), especially in terms of accuracy and efficiency of SIC. To further improve the classification performance of the current model for IoT-SD, this study aims to propose a new clustering method for optimizing the SIC of IoT-SD by combining the K-center point (K-CP) algorithm and the CFSDP algorithm.

III. SIC of IoT-SD Based on Improved Clustering Algorithm

To efficiently process these IoT-SDs, this study first fused K-CP and CFSFDP, designed a new clustering algorithm and named it Fusion Clustering Algorithm Based on K-Centroids and Fast Search of Density Peaks (FCA-KCFSDP). On this basis, an Automatic Semantic Annotation (ASA) model for IoT-SD was further designed, aiming to achieve automatic annotation of semantic information and improve the efficiency of information classification.

A. *Design of IoT-SD Clustering Algorithm Integrating CFSDP and K-CP*

In the CFSDP algorithm, local density and the minimum distance from data points to higher density points are two key basic concepts. Local density is usually measured by calculating the number of points around each point [14]. For each point, CFSDP calculates the distance from it to the closest point with higher density, which helps determine the cluster center. CFSDP typically uses a large number of samples to achieve efficient identification of cluster centers. In order to obtain more clustering centers, it is necessary to use the objective function in Eq. (1) for data selection [15].

$$Of = \sum_{i=1}^{n} p\left(obj_i, e_i\right) \tag{1}$$

In Eq. (1), Of represents the objective function. e_i represents an example of distance between multiple measurement objects. obj_i represents the measurement object. p represents the correlation between the measured object and the distance example. i represents the number of objects, and n represents the upper limit of their values. Assuming ρ_i represents local density, its calculation formulas are Eq. (2) and Eq. (3).

$$\rho_i = \sum_{j} \chi\left(d_{ij} - d_c\right) \tag{2}$$

In Eq. (2), d_{ij} and d_c represent the distance from object

obj_i to obj_j and the truncation distance, respectively. The density value $\chi(x)$ is represented by the difference between d_{ij} and d_c, and its specific value is Eq. (3).

$$\chi(x)=\begin{cases}1, x<0\\ 0, x\geq 0\end{cases} \tag{3}$$

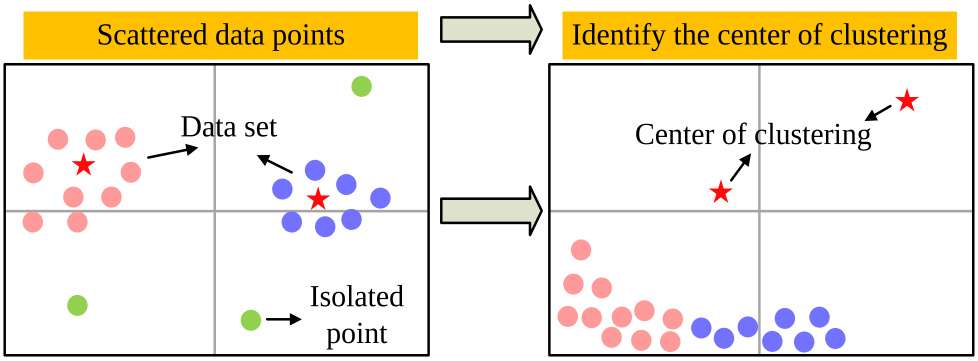
In Eq. (3), when the difference between d_{ij} and d_c is less than 0, i.e. $x<0$, the density value is $\chi(x)=1$. When the difference between d_{ij} and d_c is greater than or equal to 0, i.e. $x\geq 0$, the density value $\chi(x)=0$. Assuming that the minimum distance from a data point to a higher density point is δ_i, the calculation formulas are shown in Eq. (4) and Eq. (5).

$$\delta_i = \min \delta_i \quad \rho_j > \rho_i \tag{4}$$

In Eq. (4), when the local density ρ_j of obj_j is greater than the local density ρ_i of obj_i, the minimum distance δ_i can achieve a minimum value.

$$\delta_i = \max \delta_i \quad \rho_j \leq \rho_i \tag{5}$$

In Eq. (5), when ρ_j of obj_j is less than or equal to ρ_i of obj_i, the minimum distance δ_i can achieve a maximum value. Fig. 1 is the recognition decision diagram of the cluster center obtained by combining Eq. (1) to Eq. (5).



(a) Distribution of data before identification

(b) Distribution of data after identification

Fig. 1. Identification decision diagram of the clustering center.

Fig. 1(a) and (b) represent the distribution of surrounding data before and after cluster center recognition, respectively. Due to the high local density and minimum distance of the two pentagrams in Fig. 1(b) during the calculation process, these two points will be separately identified as outliers. And these two points happen to be the cluster centers of the two datasets in Fig. 1(a), so this method can be used to determine all the remaining cluster centers one by one. After determining all cluster centers, the remaining data will be automatically divided into nearby clusters based on the principle of nearest distance allocation. The identification formula for cluster centers is Eq. (6).

$$\gamma_i = \rho_i \times \delta_i \tag{6}$$

In Eq. (6), γ_i represents the product of local density and minimum distance. The larger the value, the more likely the data is to be the cluster center. Fig. 2 shows the running process of the CFSDP algorithm.

In Fig. 2, the execution of the CFSDP algorithm starts by calculating the local density of each data point. This step is usually achieved by quantifying the number of points within a certain radius around each point. Next, the distance from each point to the closest point with higher density and the local density value are calculated. Both local density and minimum distance serve as the axes of the decision graph to identify potential cluster centers. After determining the cluster center, the algorithm assigns the remaining points to the high-density points closest to them, forming independent clusters. Finally, to improve the accuracy of clustering, the algorithm will refine these preliminary clusters through a series of post-processing steps, and ultimately output the clustering results.

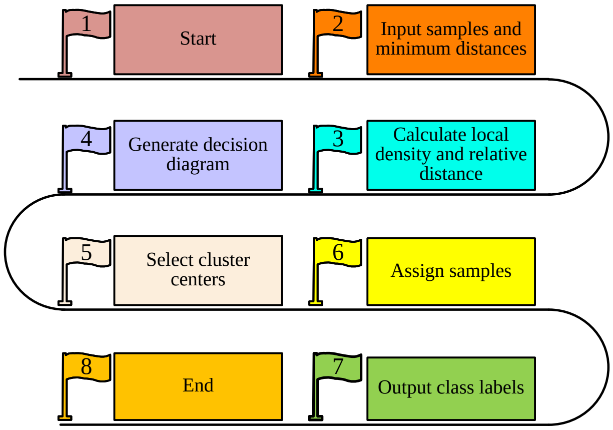

1
Start
2
Input samples and minimum distances
3
Calculate local density and relative distance
4
Generate decision diagram
5
Select cluster centers
6
Assign samples
7
Output class labels
8
End

Fig. 2. Flowchart of running the CFSDP algorithm.

K-CP is similar to the K-means algorithm, but it differs in selecting cluster centers. In K-means, the cluster center is the mean of all points within the cluster, while in K-CP, the cluster center is the actual point that exists in the data, that is, the center point. Fig. 3 is the operational diagram of K-CP.

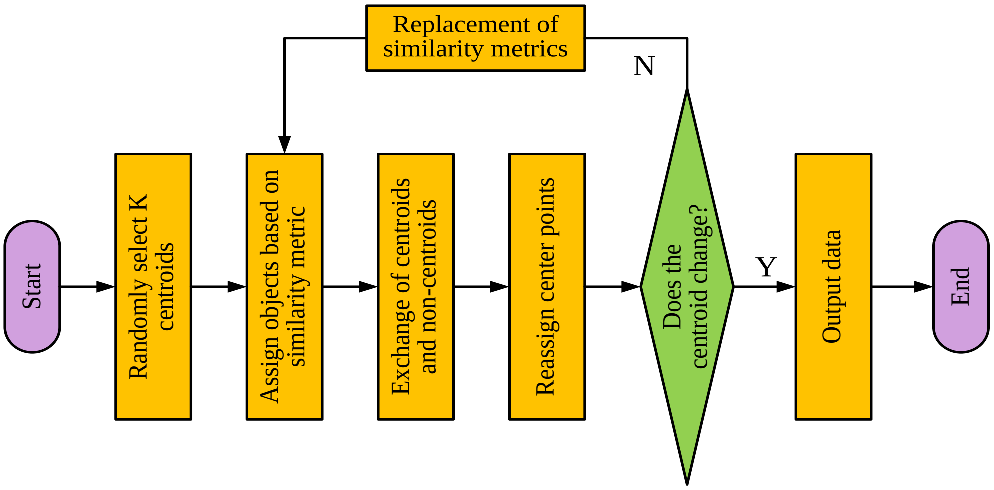

Replacement of similarity metrics
N
Start
Randomly select K centroids
Assign objects based on similarity metric
Exchange of centroids and non-centroids
Reassign center points
Does the centroid change?
Y
Output data
End

Fig. 3. Flow chart of the K-CP algorithm.

In Fig. 3, the calculation steps of K-CP are mainly divided into four parts: initializing the center point, data allocation, updating the center point, and multiple iteration algorithms. Assuming that all center point data (CPD) is denoted as m and non-CPD is denoted as o, the calculation formula for the exchange criterion function of CPD and non-CPD is Eq. (7).

$$E=\sum_{i=1}^{k}\sum_{p\in C_j} dist\left(p',o_i\right) \tag{7}$$

In Eq. (7), E represents the exchange criterion function. p' represents all objects. o_i represents an object in the C_j dataset. k represents the number of center points. To optimize the selection effect of the initial center point (ICP) of K-CP, this study adopts the dissimilarity measurement method to select the ICP, and its calculation is Eq. (8).

$$v_j=\sum_{i=1}^{n}\frac{d_{ij}}{\sum_{i=1}^{n}d_{ij}} \tag{8}$$

In Eq. (8), v_j represents the measure of dissimilarity of calculation object j. To sort the v_j values of each CPD and select the k objects with the top k minimum values as ICP.

Due to the fact that IoT-SD is usually high-dimensional, dynamically changing, and may contain noise and outliers, a single clustering algorithm is difficult to effectively handle such complex data. In order to improve the accuracy and robustness of IoT-SDSIC, this study combined CFSDP and K-CP to design FCA-KCFSDP, and its operating process is Fig. 4.

In Fig. 4, the calculation steps of the FCA-KCFSDP algorithm are mainly divided into three main steps: initialization clustering, initial cluster allocation, and cluster update. In order to optimize the FCA-KCFSDP, the study meticulously examined several key parameters, including the selection of the cluster radius, the density threshold, and the centroid selection criteria. The main rationale for selecting these parameter sets is based on the following considerations. When choosing the clustering radius, this study considered the distributional characteristics and density variations of the dataset. By comparing the effects of different radius values on the clustering results, it was ultimately found that the selected radius values could effectively differentiate between high-density regions and low-density regions, thus identifying the peak density points more accurately. In addition, the study also tried multiple radius values to evaluate their impact on classification accuracy and algorithm efficiency. The density thresholds were determined based on an in-depth analysis of the dataset features. By setting different density thresholds, it enables the final designed FCA-KCFSDP algorithm to control the tightness of clustering and thus optimize the clustering results. Different density thresholds were tried in this study, aiming to find a balance to ensure the quality of clustering while not over-dividing or merging real clusters. Finally, the choice of centroid directly affects the quality of clustering and the efficiency of the algorithm operation. The study develops a set of center point selection criteria based on the distribution characteristics and density information of the data. It is verified through pre-experiments that this set of criteria can effectively identify suitable clustering centers and improve the accuracy of clustering. In the initialization clustering stage, it is first necessary to calculate the local density and relative distance. Next, it is necessary to obtain the identification decision map of the clustering center based on the local density value, and calculate the initial clustering center based on the decision map. Then to change the center point of the cluster and calculate the distance from the object to the center point, obtaining the calculation formula for initial cluster allocation as shown in Eq. (9).

$$dist\left(a_i,a_j\right)=\sqrt{\sum_{t=1}^{n}\left(a_{it}-a_{jt}\right)^2} \tag{9}$$

In Eq. (9), a_i and a_j both represent objects. $a_{it}-a_{jt}$ represent the distance between two objects at time t. Introduce the variance of data objects as the weight factor for cluster center updates in cluster updates, and its expression is Eq. (10).

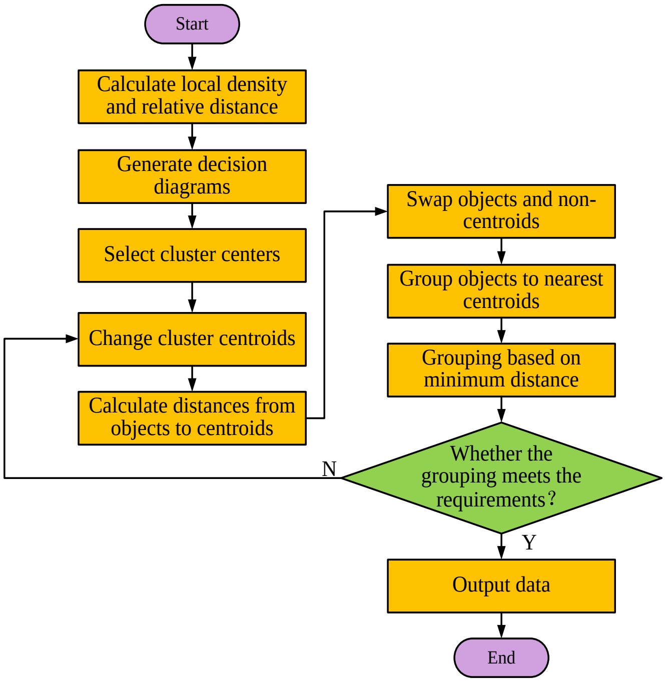

Start
Calculate local density and relative distance
Generate decision diagrams
Select cluster centers
Change cluster centroids
Calculate distances from objects to centroids
Swap objects and non-centroids
Group objects to nearest centroids
Grouping based on minimum distance
Whether the grouping meets the requirements?
N
Y
Output data
End

Fig. 4. Flowchart of running the FCA-KCFSDP algorithm.

$$\sigma_i = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n} dist\left(t_i - a_j^2\right)} \qquad (10)$$

In Eq. (10), σ_i represents variance. t_i represents the closest data object. Based on Eq. (10), Eq. (11) is introduced to measure the total distance from all nearest data objects to object a_j.

$$D_i = \sum_{j=1}^{n}\left(dist_i - a_j\right) \qquad (11)$$

In Eq. (11), D_i represents the total distance. According to Eq. (11), it is possible to update the cluster and achieve dynamic classification of data, ultimately completing the SIC of IoT data.

B. Construction of ASA Model for IoT-SD

To improve the classification efficiency of IoT-SD and further achieve automatic classification of IoT-SD, this study combined the FCA-KCFSDP clustering algorithm to build an ASA model for IoT-SD. The current ASA research mainly focuses on two methods, namely pattern based and machine learning based semantic annotation methods. For data documents with consistent formats and preprocessed data, pattern based semantic annotation methods are more effective [16-17]. This method relies on identifying patterns and implementing specific rules based on data characteristics to perform semantic annotation. On the other hand, machine learning based methods are more suitable for processing text or other unstructured data types. This type of method typically combines natural language processing technology and various machine learning algorithms for data analysis and feature extraction to reveal hidden information and knowledge in text or data. Fig. 5 shows a common ASA model structure.

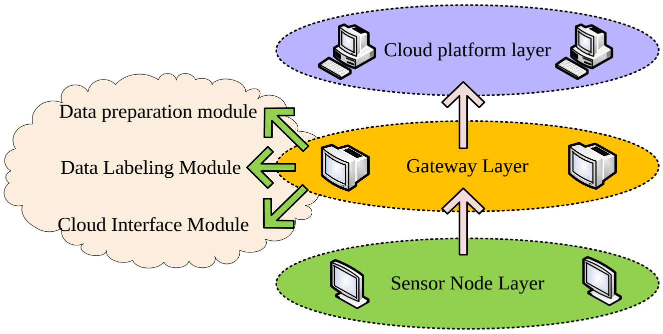


Fig. 5. Structure diagram of the traditional ASA model.

In Fig. 5, the entire ASA model consists of a cloud platform layer, a gateway layer, and a sensor node layer. The key architecture for implementing ASA is the gateway layer. In the gateway layer, it mainly includes three modules: data preparation module (DPM), data labeling module (DLM), and cloud interface module (CIM). DPM is mainly responsible for filtering and removing excess data, while converting the remaining data into XML format. This process analyzes and processes the initial data emitted by sensor nodes to minimize the computational resources required for the annotation process. Subsequently, DLM receives XML formatted data from DPM and annotates it, utilizing the concept of mapping to the application domain ontology to label the data. CIM is responsible for connecting cloud services and IoT data gateways, and implementing three main tasks. These include ensuring functional independence between the physical layer and the cloud service layer, transferring annotated IoT data to the cloud in RDF file format, processing sensor discovery content from upper layer applications, and querying requests for real-time data. The FCA-KCFSDP clustering algorithm was introduced as the core semantic classification component in the original ASA model, and the optimized structure of the IoT-SD oriented ASA model is Fig. 6.

Fig. 6 shows the ASA model with the addition of FCA-KCFSDP semantic classification component. The optimized ASA model consists of four parts, namely data pre-processing, semantic classification optimization (SCO), semantic annotation module (SAM), and CIM. Among them, the data pre-processing module aims to maintain the original functions of data aggregation, data filtering, and structured data representation. Structured data representation ensures that data is transformed in a way that is easy to process by the FCA-KCFSDP algorithm. The SCO module aims to replace the original semantic classification module with the FCA-KCFSDP clustering method. This module is responsible for assigning data to the correct semantic categories based on its characteristics and patterns. SAM will continue to receive the output of the semantic classification module and use domain ontology mapping and referencing concepts for semantic annotation of data. CIM refers to the transmission of semantically annotated data in RDF format to the cloud platform and processing of requests from the cloud platform and high-level applications. The optimized ASA model introduces the FCA-KCFSDP clustering method as the core of semantic classification, and all semantic classification work is carried out through this newly integrated algorithm. Compared to traditional ASA models, ASA models that use FCA-KCFSDP clustering method as the semantic classification core have better classification performance and adaptability. It not only enables reasonable clustering and annotation of various types of information, further reducing the need for subsequent data processing and storage, but also reduces computational costs without sacrificing performance.

IV. Results

To test the effectiveness of the research method, the results analysis section first tested the performance of the FCA-KCFSDP clustering algorithm and proved that the algorithm performed better than other comparative algorithms in error performance and SIC. Subsequently, this study applied the FCA-KCFSDP clustering algorithm to the ASA model and tested the model's performance in actual IoT-SD classification.

A. *Performance Testing of FCA-KCFSDP Clustering Algorithm*

To evaluate the performance of the FCA-KCFSDP clustering algorithm in the IoT-SD semantic classification problem, this study constructed a comprehensive dataset containing multidimensional temporal data as the experimental dataset. The data set consists of readings from different sensors, including temperature, humidity, light intensity, and motion sensor data. In addition, the data was collected from three different indoor environments, covering a duration of four weeks to ensure inclusion of various environmental changes and possible anomalies. Table I shows the specific dataset data.

Table I provides the dataset information for this study. To ensure that experimental errors caused by equipment changes can be avoided in multiple repeated experiments, this study conducted experiments in the same simulation environment. The experimental operating system is Ubuntu 20.04 LTS, with an Intel Core i7-9700K CPU @ 3.60GHz and 32GB DDR4 RAM. The algorithm design was completed using Python 3.8 and TensorFlow 2.4.1. Firstly, the changes in Mean Square Error (MSE) and Mean Absolute Error (MAE) of FCA-KCFSDP, CFSDP, and K-Means Clustering algorithms in the training dataset were compared, as shown in Fig. 7.

TABLE I. DATASET INFORMATION TABLE

Data Indicators	**Specific description**
Data Source	Indoor environment sensor data (temperature, humidity, light, motion)
Sampling Period	1 min
Total Duration	4 weeks
Number of data points	10000
Pre-processing operation	Missing value interpolation, outlier rejection, normalization
Labelling information	Provided by domain experts, contains labels such as normal, abnormal operation, equipment failure, etc.
Data division	Training set (80%), validation set (10%), test set (10%)

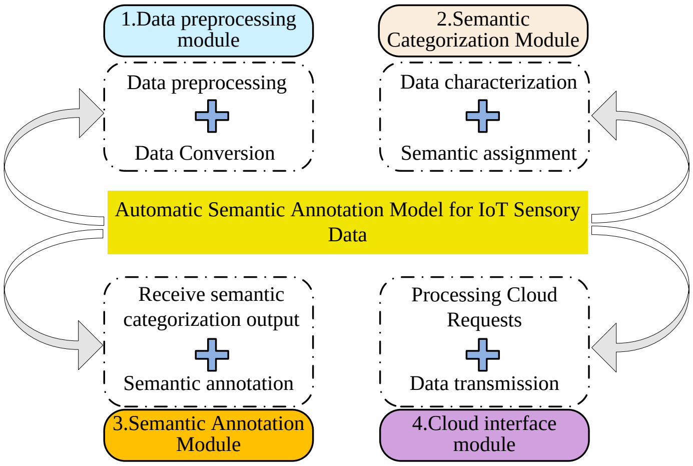
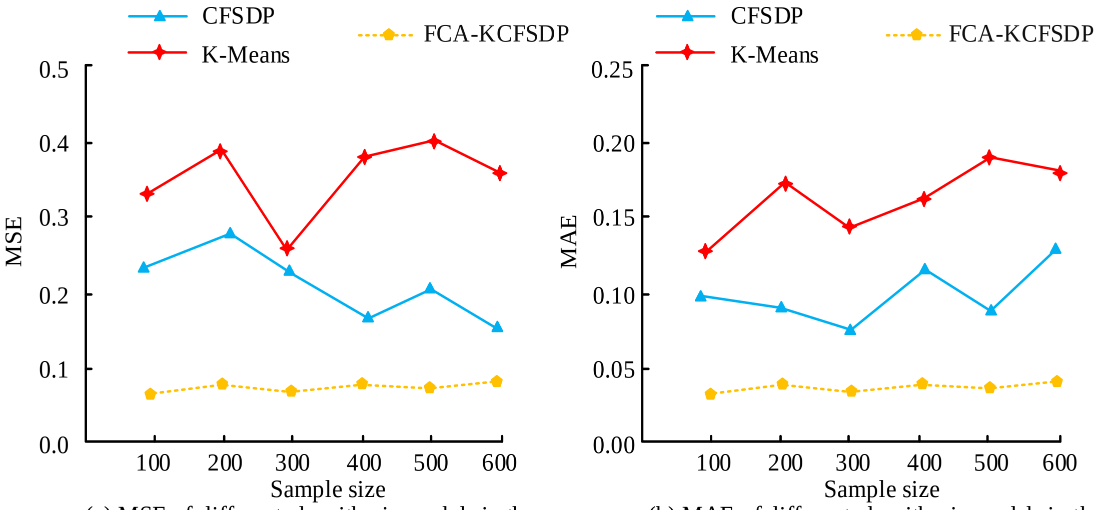

1.Data preprocessing module
2.Semantic Categorization Module
Data preprocessing
Data Conversion
Data characterization
Semantic assignment
Automatic Semantic Annotation Model for IoT Sensory Data
Receive semantic categorization output
Semantic annotation
Processing Cloud Requests
Data transmission
3.Semantic Annotation Module
4.Cloud interface module

Fig. 6. Structural diagram of the ASA model for introducing FCA-KCFSDP.



(a) MSE of different algorithmic models in the training dataset

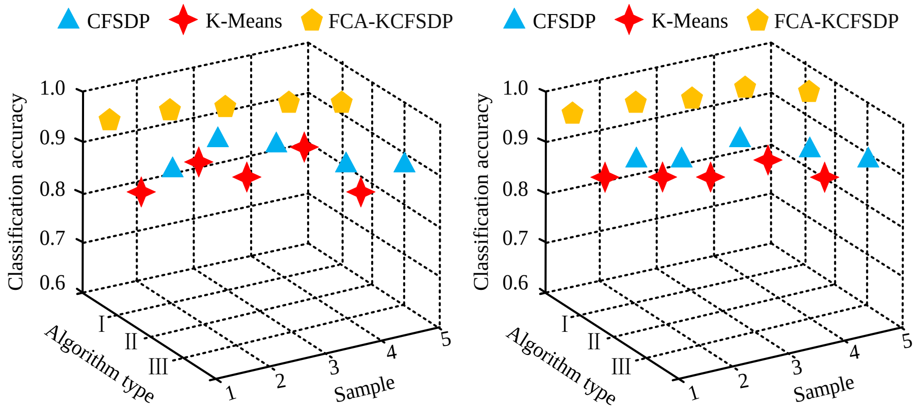
(b) MAE of different algorithmic models in the training dataset

Fig. 7. MSE and MAE for the different clustering algorithms.

Fig. 7(a) and Fig. 7(b) show the MSE and MAE values of the three clustering algorithms in the training dataset, respectively. In Fig. 7(a), as the number of training samples increases, the MSE value of the FCA-KCFSDP algorithm remains below 0.1, CFSDP is between 0.1 and 0.3, and K-Means is between 0.2 and 0.4. In Fig. 7(b), the increase in the number of training samples resulted in the MAE value of the FCA-KCFSDP algorithm always being below 0.05, CFSDP between 0.05 and 0.15, and K-Means between 0.10 and 0.20. In summary, the FCA-KCFSDP algorithm has better error performance.

Fig. 8(a) and 8(b) show the classification accuracy of the three algorithms in the training and validation sets, respectively. In Fig. 8(a), the FCA-KCFSDP, CFSDP, and K-Means algorithms have the highest classification accuracy in the training set of 0.96, 0.89, and 0.84, respectively. The highest classification accuracy of the three algorithms in Fig. 8(b) in the validation set is 0.98, 0.91, and 0.86, respectively. Therefore, the FCA-KCFSDP algorithm has higher classification accuracy in both training and validation processes, indicating that the algorithm can better perform SIC on experimental data.

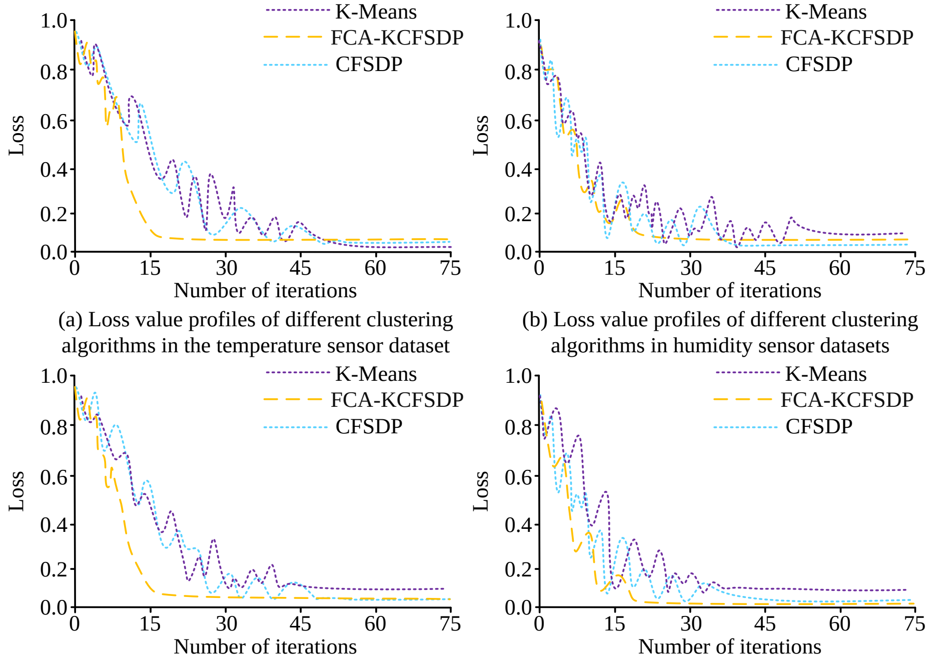
The temperature, humidity, lighting, and motion data of indoor environmental sensors are classified separately, and the loss curves of three clustering algorithms on the four classification datasets are obtained. Fig. 9(a) to Fig. 9(d) indicate that compared to CFSDP and K-Means, the FCA-KCFSDP algorithm always obtains a more stable loss curve. The FCA-KCFSDP algorithm can achieve stable classification on four datasets: illumination, temperature, motion, and humidity by iterating 15, 22, 16, and 20 times respectively.



(a) Classification accuracy of different clustering algorithms in the training set

(b) Classification accuracy of different clustering algorithms in the test set

Fig. 8. Classification accuracy of different clustering algorithms in the training and test sets.



(a) Loss value profiles of different clustering algorithms in the temperature sensor dataset

(b) Loss value profiles of different clustering algorithms in humidity sensor datasets

(c) Loss value curves of different clustering algorithms in light sensor datasets

(d) Loss value profiles of different clustering algorithms in motion sensor datasets

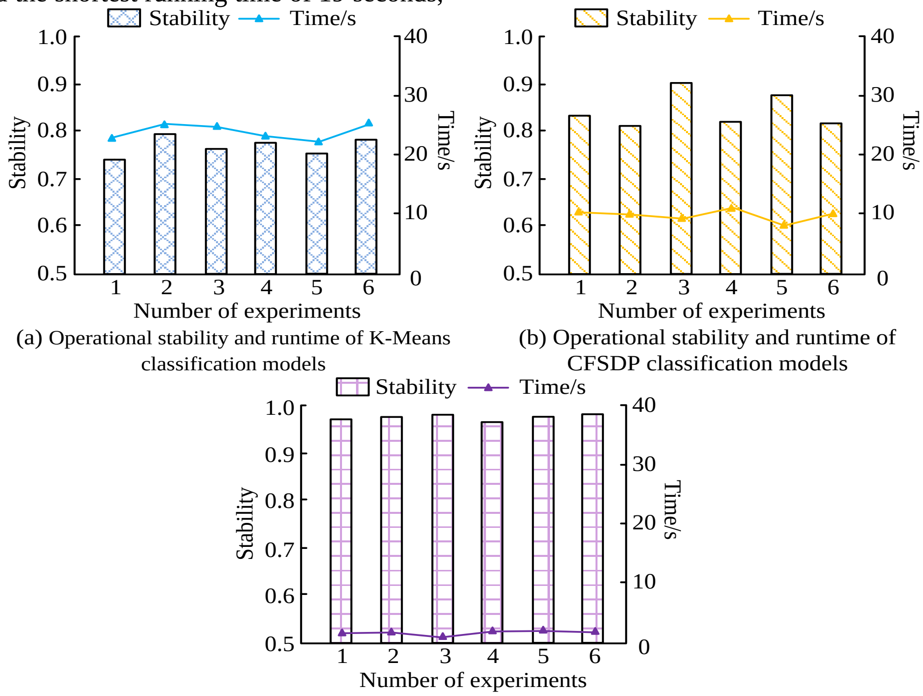
Fig. 9. Loss curves for the different clustering algorithms in the four datasets.

B. *Test of the Classification Performance of ASA Models for IoT-SD*

After testing the performance of the FCA-KCFSDP algorithm, this study applied it to the ASA model to further verify the classification performance of the IoT SDASA model optimized by the algorithm. Firstly, the operational stability and time variation of ASA models built by various clustering algorithms were compared, as shown in Fig. 10.

Fig. 10(a) to Fig. 10(c) shows the operational stability and time variation of three models under multiple actual tests. The above figure shows that the semantic annotation model combined with K-Means, CFSDP, and FCA-KCFSDP algorithms has the highest running stability of 0.79, 0.90, and 0.99, respectively, and the shortest running time of 19 seconds, 8 seconds, and 1 second, respectively. Therefore, applying the FCA-KCFSDP algorithm to the IoT-SDASA model can enable the model to have higher operational stability and shorter data classification time.

Fig. 11(a) and Fig. 11(b) show the satisfaction levels of IoT company users and experts with three different classification models, respectively. The satisfaction levels of users with the annotation models under K-Means, CFSDP, and FCA-KCFSDP algorithms are 0.76, 0.83, and 0.96, respectively. The satisfaction rates of experts with the models under K-Means, CFSDP, and FCA-KCFSDP algorithms are 0.72, 0.86, and 0.95, respectively.

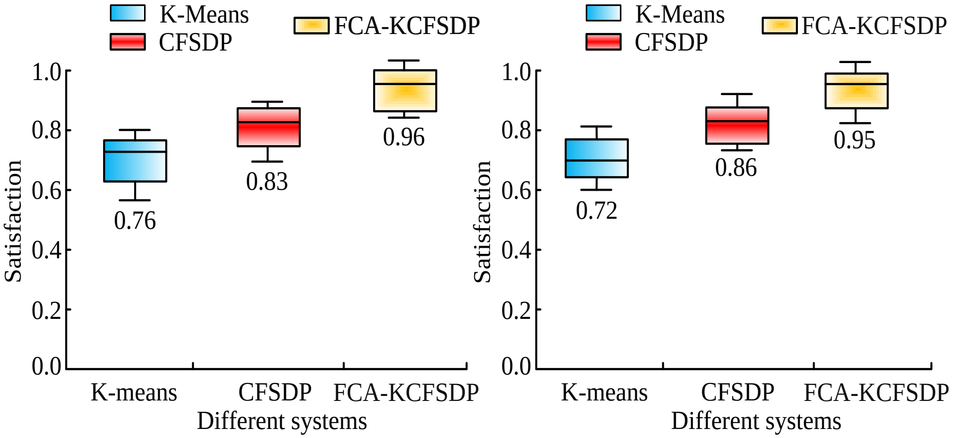


(a) Operational stability and runtime of K-Means classification models

(b) Operational stability and runtime of CFSDP classification models

(c) Operational stability and runtime of FCA-KCFSDP classification models

Fig. 10. Stability and running time of each classification model.



(a) User satisfaction with classification models

(b) Expert satisfaction with classification models

Fig. 11. Satisfaction of users and experts with the classification model.

The classification effects of four different clustering algorithms in practical applications are given in Table II. One week's IoT sensing data was collected from an enterprise, which was divided into noisy data and non-noisy data, and 1,000 of each was taken. In Table II, the classification accuracy and classification time of K-Means algorithm are 84.25% and 1.87s for noisy data, and 86.32% and 1.59s for non-noisy data, respectively. The classification accuracy and classification time of CFSDPs algorithm are 88.30% and 1.38s for noisy data, and 88.30% and 1.38s for non-noisy data, respectively. The classification accuracy and time were 89.94% and 1.26s for noisy data. k-means++ algorithm was 91.05% and 1.12s for noisy data, and 92.17% and 1.05s for non-noisy data. fca-KCFSDP algorithm was 98.49% and 1.59s for noisy data. Classification time is 98.49% and 0.25s for noisy data, and 98.85% and 0.21s for non-noisy data. Taken together, all the clustering algorithms are better at dealing with noisy data than non-noisy data, and the FCA-KCFSDP algorithm, compared to the other three comparative algorithms, has higher classification accuracy and classification efficiency.

TABLE II. ACTUAL CLASSIFICATION EFFECT OF DIFFERENT ALGORITHMS

Algorithmic models	Data Type	Classification accuracy	Classification execution time
K-Means	Noise data	84.25%	1.87s
	Non-noise data	86.32%	1.59s
CFSDP	Noise data	88.30%	1.38s
	Non-noise data	89.94%	1.26s
K-means++	Noise data	91.05%	1.12s
	Non-noise data	92.17%	1.05s
FCA-KCFSDP	Noise data	98.49%	0.25s
	Non-noise data	98.85%	0.21s

V. CONCLUSION

In response to the shortcomings of low classification accuracy and poor classification performance of the current IoT SDSIC tool, this study combined the K-CP and CFSDP algorithms to design an optimized FCA-KCFSDP, and used it to build an ASA model for IoT-SD. The research results indicate that compared to K-means and CFSDP algorithms, FCA-KCFSDP clustering algorithm had better error performance, with MAE and MSE below 0.05 and 0.1, respectively. In addition, the classification accuracy of FCA-KCFSDP, CFSDP, and K-means algorithms in the entire dataset could reach up to 0.98, 0.91, and 0.86, respectively. The sensor data in the dataset was subdivided into four types of data: motion, humidity, temperature, and lighting. It was found that the FCA-KCFSDP algorithm can reach a stable state by iterating 15, 22, 16, and 20 times respectively. Therefore, the performance of FCA-KCFSDP algorithm was superior to the other two comparative algorithms. Finally, this study also compared the stability and running time of classification models under K-means, CFSDP, and FCA-KCFSDP algorithms, and found that their highest running stability reached 0.79, 0.90, and 0.99, respectively, and their shortest running time was 19 seconds, 8 seconds, and 1 second. The FCA-KCFSDP classification model could also achieve higher classification satisfaction. In summary, the clustering algorithm and classification model designed in this study can achieve good semantic classification results. Subsequent research can further expand the types of semantic information in the dataset, thereby proving that the model has better generalization properties. Future research work includes the following points. Firstly, explore the possibility of integrating density peak based fast search clustering algorithms with deep learning models to improve the accuracy and efficiency of the model when dealing with complex datasets. Secondly, the research will be extended to more application areas, such as intelligent transportation systems, environmental monitoring, etc., to verify the universality and applicability of the algorithm. In addition, focus on security and privacy protection during data processing, and study how to ensure algorithm performance while ensuring data security and user privacy are not compromised.

ACKNOWLEDGEMENT

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Structure-Aware Scheduling Algorithm for Deadline-Constrained Scientific Workflows in the Cloud

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Abstract—**Cloud computing provides pay-per-use IT services through the Internet. Although cloud computing resources can help scientific workflow applications, several algorithms face the problem of meeting the user's deadline while minimising the cost of workflow execution. In the cloud, selecting the appropriate type and the exact number of VMs is a major challenge for scheduling algorithms, as tasks in workflow applications are distributed very differently. Depending on workflow requirements, algorithms need to decide when to provision or de-provision VMs. Therefore, this paper presents an algorithm for effectively selecting and allocating resources. Based on the workflow structure, it decides the type and number of VMs to use and when to lease and release them. For some structures, our proposed algorithm uses the initial rented VMs to schedule all tasks of the same workflow to minimise data transfer costs. We evaluate the performance of our algorithm by simulating it with synthetic workflows derived from real scientific workflows with different structures. Our algorithm is compared with Dyna and CGA approaches in terms of meeting deadlines and execution costs. The experimental results show that the proposed algorithm met all the deadline factors of each workflow, while the CGA and Dyna algorithms met 25% and 50%, respectively, of all the deadline factors of all workflows. The results also show that the proposed algorithm provides more cost-efficient schedules than CGA and Dyna.**

Keywords*—*Workflow scheduling; workflow structure; cloud computing; resource provisioning; deadline constrained; infrastructure as a service

I. Introduction

Cloud computing has become a significant platform for executing workflows as it allows the rental of resources on demand. It uses a pay-as-you-go billing model to provide IT resources over the internet [1]. This is done by renting virtual machines (VMs) with predefined CPU, memory, storage and network bandwidth capacities. To meet a wide range of application needs, customers can access various computing resources (i.e. VM sets) at different prices. Clouds offer infinite computing resources with different configurations that can be rented and used as needed. This architecture requires resource provisioning heuristics that run concurrently with a scheduling algorithm, which determines the amount and type of VMs to request from the cloud and the optimal time to rent and provision them.

Cloud computing today enables the execution of scientific applications consisting of hundreds or thousands of interdependent tasks [2]. Montage [3], CyberShake [4] and LIGO [5] are scientific workflow applications used in astronomy, earthquake science, and gravitational physics, respectively. A task does not begin its execution until all its predecessor tasks have been completed. Most of these scientific applications are built as workflows, which are groups of computational tasks linked by control and data dependencies. Each workflow phase consists of a different number of tasks, each requiring a different amount of computing resources. Depending on the application, a workflow can be extremely CPU-intensive and/or data-intensive. The complexity of task execution can vary from sequential execution to highly parallel execution with many inputs from different tasks.

The objective of the workflow scheduling problem in the cloud is to map tasks to resources to maintain task precedence while achieving certain performance metrics [6]. In the cloud, faster and more powerful computing resources are often more expensive than slower ones. As a result, using powerful computing resources can increase execution costs by shortening workflow execution time. Consequently, the trade-off between time and cost is a major challenge for cloud-based workflow scheduling [7]. Two typical approaches are used to solve this: reducing the total execution time under a budget constraint [8] and reducing the financial cost under a time constraint [9]. This study presents an approach to the problem of time-constrained workflow scheduling. The objective is to develop a workflow schedule for a given workflow that reduces the monetary cost of running the workflow in the cloud within a given time limit.

Creating an optimal schedule in a heterogeneous cloud environment is NP-hard [10]. On the other hand, workflow scheduling aims to reduce the overall time. Consequently, no algorithm can achieve an ideal solution in polynomial time, while certain algorithms can provide approximate results in polynomial time. Therefore, heuristics are required to find near-optimal solutions effectively.

In a cloud computing environment, it is challenging to select the type and amount of resources to use for the cost-effective execution of scientific workflows [6]. A shorter execution time can be achieved using many resources, but this could come at a significant financial cost. In recent years, a significant amount of research has been conducted on algorithms for scheduling scientific workflows, which are essential for maximising the benefits of cloud computing. However, these algorithms must focus not only on assigning tasks to resources but also on determining the amount and type of resources to be used (i.e., provisioning resources) during the execution of the workflow [11]. Moreover, it is necessary to determine when these resources should be provisioned and when they should be de-provisioned during the workflow execution.

In this study, we present a Deadline and Structure-Aware Workflow Scheduler (DSAWS), which is a heuristic. The algorithm is a static assignment of tasks to VMs with an elastic VM pool that provisions and de-provisions VMs for scheduling tasks as the workflow executes. The algorithm analyses the workflow structure to determine the type and amount of VMs to deploy and when to provision and de-provision them. The algorithm's first phase (the planning phase) selects the number and type of VMs to be used and the allocation of tasks to these resources. In the second phase, the algorithm provisions the VMs selected in the planning phase at the specified times. It also releases these VMs based on the times set in the first phase, considering the delay in provisioning/de-provisioning a VM in the cloud. Its main objective is to use these resources effectively to keep costs down without compromising deadlines.

We evaluated our algorithm using well-known workflows such as Montage, CyberShake, Inspiral, and Epigenomics, as this makes our results comparable to future studies. Finally, the experimental results of the DSAWS algorithm are compared with different scheduling algorithms such as Dyna[12] and CGA[16].

This approach reduces the overall execution cost of a workflow while meeting a user-defined deadline. Experimental results show that DSAWS outperforms other state-of-the-art algorithms in terms of meeting workflow deadlines while reducing execution costs. The experiments have shown that DSAWS delivers more cost-efficient schedules for various workflow applications than Dyna and CGA.

The remainder of the work is arranged as follows: Section II provides background information and reviews related work on workflow scheduling. The details of the design and implementation of the DSAWS algorithm are described in Section III. The experiment results are shown and discussed in section IV. Section V concludes the paper and future work.

II. Background Knowledge and Related Works

In this section, the presentation of scientific workflows is presented first. Then, related work on workflow scheduling with a problem statement on the clouds.

A. Background Knowledge

A workflow can be represented as a directed acyclic graph (DAG) consisting of a collection of atomic tasks. As shown in Fig. 1, the vertices of the workflow are a set of tasks $\{t_1, t_2, ..., t_n\}$, while the workflow edges represent data dependencies between these tasks. For example, during the execution of the workflow, the successor task t_4 waits for its predecessor task t_1 to complete its processing and produce its output data. When t_1 finishes, some of its data outputs become input dependencies for t_4. When t_4 is scheduled, its data input dependencies are sent to its target host to enable the successful execution of t_4.

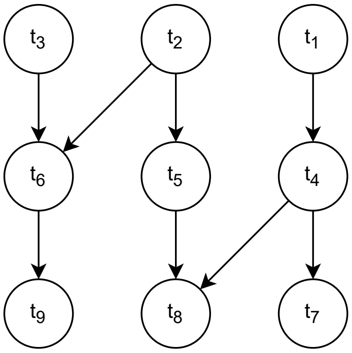

Fig. 1. A sample workflow.

B. Related Works

Many scheduling algorithms have focused on reducing the execution time of workflow applications in cloud computing. Heuristics and meta-heuristics-based approaches have been studied for the workflow scheduling problem.

Genetic algorithms (GA) [13] and Particle Swarm Optimisation (PSO) [14] are well-known meta-heuristic techniques. Moreover, meta-heuristic techniques such as GA and PSO can be found in the literature for workflow scheduling in the cloud. Verma et al. [15] presented a genetic algorithm that schedules cloud-based workflows depending on their importance to reduce the execution cost while meeting the workflow deadline. However, this algorithm does not consider the virtual machines' start-up time in the cloud. The paper [16] presents a genetic algorithm for deadline-constrained scheduling of workflows using the co-evolution technique to modify crossover and mutation probabilities to accelerate convergence and prevent prematurity. These approaches have the potential to be implemented in a cloud environment, although the waiting time might require the use of a computationally intensive meta-heuristic optimisation technique. The pre-processing duration may increase as the workflow size increases, leading to significant queuing delays.

Several heuristic algorithms [17], [18], [19], [20], [21] in the cloud computing environment are presented for workflow scheduling. Saeid et al. [20] presented a deadline-constrained approach for scheduling workflows that allocates an entire critical path to a single VM instance to reduce data transfer time between successive jobs. This technique does not consider allocating jobs from a single path to many VM instances in search of better scheduling options. This technique also does not consider the time it takes a provisioned VM instance to send all output data to the local storage of the VMs running the child tasks before it is de-provisioned. This is not practical during the period of process execution.

Xiumin et al. [22] have proposed a technique for extending HEFT [23]. It uses a two-step approach to reduce workflow makespan and execution costs simultaneously. However, it does not consider the startup time of a VM instance or the actual data transfer time between successive jobs. This algorithm selects the final scheduling solution from the K best solutions. However, the optimal determination of the value of K is not addressed. In the meantime, comparing the K scheduling solutions to choose the best one results in the scheduling algorithm's inefficiency.

The Coevolutionary Genetic Algorithm (CGA) [16] was proposed based on the biological evolutionary method (genetic algorithm), where the adaptive penalty function for strict deadlines was introduced. It assigns partial deadlines to each task and executes them on currently rented or existing VMs to reduce the total cost. CGA was chosen for comparison in our evaluation because of its static approach, which has the potential to generate optimal solutions. Nevertheless, our main interest is to compare DSAWS with CGA when both algorithms can meet deadlines. Moreover, by considering these algorithms, we can evaluate the adaptability of our results and show how DSAWS can meet deadlines while other algorithms fail to meet deadlines.

Dyna [12] is a scheduling technique developed with autoscaling capabilities for the cloud to dynamically provision and de-provision VMs depending on the current state of tasks. It was presented to develop a scheduling system that reduces the expected monetary cost under user-defined probabilistic scheduling constraints. It selects VM types for each workflow task based on an A-star search to reduce costs. It is designed to schedule many workflows simultaneously but can also be modified to schedule only one. Dyna was chosen for comparison in our evaluation because the algorithm is periodically improved by adjusting the number of VMs requested in each category to ensure timely completion of tasks at a lower cost. The aim is to show how the static component of DSAWS enables the creation of schedules that outperform the Dyna algorithm in terms of meeting workflow deadlines while reducing execution costs.

ARPS [24] is an algorithm for adaptive resource provisioning and scheduling for scientific workflows in Infrastructure as a Service (IaaS) clouds. It was designed to address cloud-specific issues such as unlimited on-demand access, heterogeneity, and pay-per-use (i.e., per-minute billing). Consequently, their strategy was also designed to consider a user's deadline and reduce the cost of the environment by using the resource provisioning and scheduling service. Finally, the experimental results show that they perform a workflow more effectively than other sophisticated algorithms to meet deadlines and reduce costs.

Mao et al. [25] proposed a workflow scheduling heuristic for the cloud environment that allows them to dynamically generate the lowest schedule while meeting the user's deadline. They investigated multiple VM types and cloud characteristics, such as alternative pricing models and acquisition delays. However, they did not consider data transfer time between linked jobs, which is one of the most important criteria and significantly impacts data-intensive workflows.

By analysing the workflow structure, [30] proposes a resource provisioning and scheduling technique that determines the required number and configuration of VMs. They claimed that their approach addresses data-intensive workflows to minimise data transfer. However, they did not consider the data transfer time between tasks during the execution of the two examples presented, which is one of the most important factors and significantly impacts workflow execution time. In addition, they neglected resource provisioning and deprovisioning delays in their experiments.

Researchers in [26] have presented a two-step method for provisioning cloud resources for workflows by minimising makespan and wastage of resources based on their structural characteristics. The proposed method considers the nature of the tasks, which may be computational, memory-, or storage-intensive. The performance of the presented algorithm is evaluated using five scientific workflows as benchmarks. Simulation results show that the proposed method outperforms two existing algorithms for each workflow.

Although there are several workflow scheduling techniques, there is a need for resource estimation for workflow execution because the above approaches have not analysed the workflow structure in depth. In this paper, we propose DSAWS, which is a complete full-ahead scheduling algorithm that considers the structure of the workflow. We discuss a method to deal with under- and over-provisioning issues.

III. The Proposed Scheduling Algorithm

Several objectives associated with task scheduling issues need to be addressed. The approach suggested in this paper focuses on running workflow applications in a cloud environment to lower overall execution costs while still meeting the user-set deadline. The proposed technique analyses the workflow structure, determines the number of tasks at each level, and provides a rank value for all workflow tasks. To determine the quantity and configuration of resources needed to complete the workflow execution by the user-set deadline, use this rank value.

Two approaches are discussed. First, in the planning phase, the exact number and configuration of VMs that need to be rented from cloud service providers are determined based on the deadline constraint and the ranking value of the tasks. It also uses the remaining time (leftover time) in the current billing period to avoid wasting resources. The plan to reuse cloud resources can eliminate the need for further provisioning and deployment costs.

The second approach concerns the execution phase (the second phase). It aims to provision or de-provision the resources of the selected services for tasks in the planning phase. These resources are maintained until they have completed all the previously assigned tasks. However, if some resources are not needed for the subsequent tasks, they are terminated immediately after the output data is transferred. This significantly reduces execution time and resource costs, which is crucial for workflow users. We will explain the steps of Algorithms 1 and 2 in the next paragraph using Table I, which contains the notations used in our algorithms.

Algorithm 1 calculates the rank value of each task, starting with the exit tasks (tasks without any child). First, the runtime of each exit task became its rank value for those tasks that have no child tasks (lines 2-6), and then the rank value is assigned to the parent tasks of the exit tasks (lines 7-15), which involves calling Algorithm 2 (line 11).

Second, Algorithm 2 assigns to each parent task the maximum rank value of the rank values of its child tasks (lines 2-8) with the maximum data size of the data sizes of its child tasks (lines 9-12). Algorithm 2 continues assigning the rank value

TABLE I. NOTATIONS FOR THE SYMBOLS USED IN THE ALGORITHMS

Notations	Meanings
$T(G)$	Set of tasks in workflow graph.
D	User-defined deadline of the workflow.
E	Set of edges between tasks in workflow.
t_{entry}	Task without any parent.
t_{exit}	Task without any child.
t_{EST}	Earliest Start Time of task t.
t_p	Predecessors (parents) of task t.
p_p	Predecessors of predecessor p.
t_{ch}	Successors (children) of task t.
$t_{runtime}$	Runtime of task t.
t_{rank}	Rank value of task t.
$readyList$	List of the ready tasks in workflow.
$rankList$	List of all tasks in descending order of their rank values.
s^{speed}	Performance capacity of service type s.
vm^{speed}	Performance capacity of virtual machine vm.
$VMsList$	List of selected VMs with scheduled tasks on them during the planning phase.
m	Number of VM types.
n	Number of currently leased VMs.
vm_{start}	Start time of virtual machine vm.
vm_{stop}	Stop time of virtual machine vm.
$vm_{idleTime}$	Idle time of virtual machine vm.
$vm_{billingPeriod}$	Billing period of virtual machine vm.
$t_{transferTime}$	Transfer time of all output data of task t to the VMs of its successors ch.

Algorithm 2 Task Ranking

```
1:  procedure TASKRANK($p$)
2:      $ch_{maxRank}$ := 0
3:      $ch_{maxData}$ := 0
4:      for each child $ch$ of $p$ do
5:          if $ch$ has rank value then
6:              if $ch_{rank} > ch_{maxRank}$ then
7:                  $ch_{maxRank}$ := $ch_{rank}$
8:              end if
9:              if $ch_{data} > ch_{maxData}$ then
10:                 $ch_{maxData}$ := $ch_{data}$
11:             end if
12:         end if
13:     end for
14:     $p_{rank}$:= $p_{runtime}$+$maxRank$+$maxData$
15:     if $p$ has parent then
16:         for each parent $p_p$ of $p$ do
17:             call TaskRank($p_p$)
18:         end for
19:     end if
20: end procedure
```

for each task recursively until it reaches the entry tasks that have no parent tasks (lines 15-19). Finally, after Algorithm 2 completes its steps, Algorithm 1 sorts all tasks in descending order according to their rank values to determine the order in which workflow tasks should be scheduled (line 16). In the next paragraphs, we will explain the steps of the Algorithms 3 and 4.

Algorithm 1 Workflow Ranking

```
1:  procedure ASSIGNRANKING($T(G)$)
2:      for all $t \in T(G)$ do
3:          if $t$ has no children then
4:              $t_{rank}$:= $t_{runtime}$
5:          end if
6:      end for
7:      for all $t \in T(G)$ do
8:          if $t$ has no children then
9:              for each parent $p$ of $t$ do
10:                 if $p$ has no rank value then
11:                     call TaskRank($p$)
12:                 end if
13:             end for
14:         end if
15:     end for
16:     Arrange all tasks in the list $rankList$ in decreasing
        order of rank values.
17: end procedure
```

The pseudocode of the entire DSAWS algorithm for workflow scheduling is shown in Algorithm 3. The proposed algorithm uses the rank value to support each task by selecting the appropriate VM to execute it within the deadline. In the first phase, the algorithm selects the appropriate type and the exact number of VMs needed to execute workflow tasks to meet the deadline set by the user. After the basic initialisation in lines 2-8 of Algorithm 3, it receives the workflow tasks arranged from Algorithm 1 while the deadline D is set by the user. Line 2 identifies the available instance types of VMs the service provider offers. In line 3, the rented set $rentedVMs$ is empty at the beginning of the execution of the algorithm. We have initialised a variable called $success$ that changes when a task finds its matching VM to meet the deadline. In line 6, $vm_{minTime}$ is the earliest available VM time in the currently leased VMs. In line 7, although all tasks are arranged in descending order of their rank values, Algorithm 3 selects ready tasks from the $rankList$ and adds them periodically to the $readyList$ in order. In line 8, $timeLine$ is the difference between the earliest available time of the VM or the earliest start time of a task and a deadline D. The while loop in line 9 is used to find a suitable VM for each task in the workflow. In line 12, the $timeLine$ is the difference resulting from subtracting $vm_{minTime}$ from the deadline because the task begins its execution by selecting a VM instance that has already been rented. First, the ready tasks check the available rented VMs to meet the deadline. If a task does not find a suitable VM to meet the deadline, it selects a new suitable VM to meet the deadline. At the beginning of the execution of the algorithm, there are no rented VMs in line 13. Therefore, the algorithm skips lines 13-20. In line 22, the $timeLine$ is the difference resulting from subtracting the earliest start time of a task (t_{EST}) from the deadline since the task begins its execution by selecting a new VM instance. Line 23 tries to select a new VM by comparing $timeLine$ with the task's rank value divided by the VM speed (lines 13 and 23). For cost-effective task scheduling, the task searches for a VM at the service provider, starting with the slowest VM until it reaches the appropriate VM that meets the deadline (lines 24-25). In line 26, the task is removed from the unscheduled $readylist$, while in line 28, the selected new VM is added to the set of rented VMs ($rentedVMs$). The algorithm updates the EST for all successors of a task (line 16 or 27) after finding a suitable resource in line 15 or 25. This update may change the readiness of the tasks based on the completion time of their predecessor tasks. When all tasks are assigned to VMs, the algorithm calls Algorithm 4 in line 33.

Algorithm 4 shows the pseudocode of the TimelineVMS algorithm for provisioning and de-provisioning resources. In the second phase, the algorithm first determines the time for provisioning the VMs and the time at which each VM is de-provisioned by taking into account the delays in provisioning and de-provisioning a VM in the cloud. Second, the algorithm determines the idle time between two scheduled, consecutive tasks on each VM. During the execution of the workflow, the algorithm dynamically adds and removes resources from its pool.

Algorithm 3 The DSAWS scheduling algorithm

```
procedure DSAWS(G($T$,$E$),$D$)
    $m$= available instance types of VMs ($S$)
    $rentedVMs = \varnothing$ the currently leased virtual machines
    $success$ = false.
    $vm_{booting}$ = the booting time of VM
    $vm_{minTime}$ = the earliest available time of $vm$ in $rentedVMs$.
    $readyList$ = receives repeatedly ready tasks from $rankList$.
    $timeLine$ = represents the difference of subtracting $vm_{minTime}$ or $t_{EST}$ from the deadline $D$.
    while (there exists unscheduled $t$ in $readyList$) do
        $t$ = find the earliest EST in $readyList$
        $vm_{minTime}$= find the earliest available time of $vm$ in $rentedVMs$.
        $timeLine$ := $D$ - $vm_{minTime}$
        for all $vm_j \in VM$ do where $j = 1, 2, \dots, n$
            if $timeLine >= \frac{t_{rank}}{vm_j^{speed}}$ then
                select $vm_j^{speed}$ to run $t$
                update EST for all successors of $t$
                remove $t$ from $readyList$
                $success$ := true
            end if
        end for
        if success==false then
            $timeLine$ := $D$ - $t_{EST}$
            for all $s_i \in S$ do where $i = 1, 2, \dots, m$
                if $timeLine >= (\frac{t_{rank}}{s_i^{speed}})$ then
                    select a new instance $vm_i^{speed}$ to run $t$
                    remove $t$ from $readyList$
                    update EST for all successors of $t$
                    add $vm_i^{speed}$ to $rentedVMs$
                end if
            end for
        end if
    end while
    call TimelineVMs(VMs)
end procedure
```

Algorithm 4 represents the second phase, where workflow tasks are scheduled on the selected resources ($VMsList$) during the planning phase. It receives from Algorithm 3 a schedule for all tasks about the types and number of their VMs ($VMsList$). After initialisation in lines 2-5, the booting and shutdown times of resources and the VM's billing period are set. In line 5 of the algorithm, $vm_{idleTime}$ is used to find the idle time between any two scheduled consecutive tasks on a VM to shut down this VM.

Algorithm 4 Provisioning resources

```
 1: procedure TimelineVMs($VMsList$)
 2:     $vm_{booting}$ = the booting time of VM
 3:     $vm_{shutdown}$= the de-provisioning time of VM
 4:     $vm_{billingPeriod}$ = the billing period for VM
 5:     $vm_{idleTime}$= the idle time between two consecutive tasks on the VM.
 6:     for all $vm \in VMsList$ do
 7:         for each task $t$ on $vm$ do
 8:             if $vm$ has not provisioned then
 9:                 $vm_{start}$=($t_{start} - vm_{booting}$)
10:                 if $vm_{start} < 0$ then
11:                     $vm_{start}$=0
12:                 end if
13:                 provision $vm$ on the time of $vm_{start}$
14:             end if
15:             $vm_{idleTime}$= $vm_{idleTime}$ - $vm_{shutdown}$
16:             if $vm_{idleTime} >= vm_{billingPeriod}$ then
17:                 transfer output data of $t$ to the VMs of its successors.
18:                 $vm_{stop}$= $t_{end}$+$t_{trasferTime}$
19:                 de-provision $vm$ on the time $vm_{stop}$
20:             end if
21:         end for
22:         transfer output data of $t$ to the VMs of its successors.
23:         $vm_{stop}$= $t_{end}$+$t_{trasferTime}$
24:         de-provision $vm$ on the time $vm_{stop}$
25:     end for
26: end procedure
```

To do this, the VM's billing period is taken into account to determine whether the idle time is greater than the billing period of a VM. For example, if workflow tasks are scheduled on VMs in the first phase, the algorithm determines when to start a VM and when to shut it down in the second phase by checking the schedule of the tasks on their VMs. This reduces the idle time of VMs and gaps in scheduling between workflow tasks. In lines 6 and 7, the algorithm identifies the tasks of each VM by reading the start and end times of each task on it. The algorithm then attempts to prepare tasks' resources before the tasks begin their execution (lines 9-12), as the provisioning process is still significant due to the overhead associated with leasing virtual machines (lines 8–14). The consequences of VM provisioning and de-provisioning delays are greatly mitigated and are much easier to manage.

First, the algorithm uses resource elasticity to meet the user's deadline but knows when to rent and release resources. If a new VM needs to be provisioned during the execution of the workflow, the algorithm can start VMs earlier before the task starts by taking into account the delay in provisioning a VM instance to speed up the execution of the workflow because provisioning a VM takes time. Secondly, it uses the cloud billing model to optimise resource utilisation while reducing the number of rented resources. It also tries to schedule tasks on currently rented VMs to reduce the need for further VM provisioning costs.

Furthermore, the algorithm checks the timeline of each VM to see if the idle time is greater than the instance's billing period (lines 16-20). It then sends the output data to the VMs performing the successor tasks (line 17) before de-provisioning that VM instance in line 19. Finally, it sends the output data to the VMs executing the successor tasks, if any (line 22), before de-provisioning that VM instance in line 24 because the VM has completed its tasks.

A. An Illustrative Example

To illustrate how the proposed algorithm works, we apply its steps to a sample workflow shown in Fig. 2. The workflow consists of nine tasks in the nodes of the graph: $t_1 - t_9$. The value within the node of each task indicates the estimated time of its execution (in seconds), while the number in parentheses represents the rank value. The estimated time for data transfer between VMs is also shown on the edges between nodes.

The following sections explain how to use the new algorithm to perform the workflow. Before the algorithm starts, the rank value for all tasks should be calculated using Algorithms 1 and 2. Then the tasks are sorted in descending order of their rank value. We assume that the cloud provider offers three types of VM computing services (vm^1, vm^2 and vm^4) to execute the workflow tasks. The billing period for computing services is set to 10 seconds, and the costs for vm^1, vm^2 and vm^4 are 2, 4 and 6 respectively. The speeds for vm^1, vm^2 and vm^4 are 1, 2 and 4, respectively. The VM instance provisioning and shutdown delays are set to 2 and 1 second, respectively, and the workflow deadline is set to 35, which is the maximum rank value (32) in the workflow, plus the provisioning (2) and de-provisioning delays (1).

For the example workflow in Fig. 2, we call the DSAWS scheduling algorithm, i.e., Algorithm 3. At the beginning of the workflow execution, $t_1 - t_3$ are the ready tasks that need to be scheduled and steps 13-20 of Algorithm 3 are not applied since no VMs have been provisioned yet. Therefore, steps 21-31 are executed, running the for loop in line 23 one or more times until each task finds its appropriate resource (s_1^1) to execute that meets the user's deadline. The value EST is calculated for the successor tasks of t_2 in step 25.

Steps 13-20 can be executed if some resources are available. A task checks the available rented resources (vm_1^1), starting with the slowest and then the fastest (in ascending order by speed). If a task (t_1) does not find a suitable resource that completes execution within the deadline, it decides to start a new instance of available services (s_2^1) considering the speed of the resource in step 24. Similarly, t_3 will select a new instance (s_3^1) that can complete execution within the deadline. Table II shows the scheduled tasks, the selected VMs, and the execution time (in seconds) of each task.

Step 1: First, the DSAWS algorithm assigned t_2, t_1, and t_3 to vm_1^1, vm_2^1, and vm_3^1, respectively. The algorithm started three VMs to meet the user's deadline, and the current simulation time was two due to the VM booting time.

Step 2: The algorithm assigned t_5 to the available instance vm_1^1, so no data transfer occurred. The same is occurred for steps 3 and 4: t_4 and t_6 were assigned to the instances of their predecessor tasks vm_2^1 and vm_3^1, respectively. Finally, the last three steps used the same available instances of their predecessor tasks without data transfer. After all, tasks have been scheduled. The next step is called Algorithm 4 in step 33 to provision and de-provision the resources of the services assigned to the tasks during the previous phase (the planning phase).

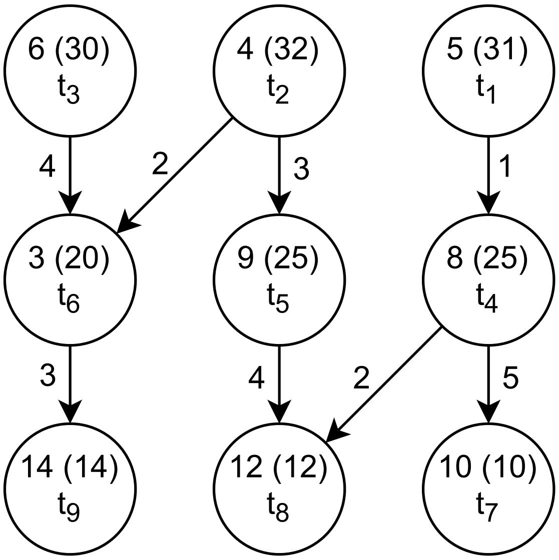

Fig. 2. A sample workflow.

Finally, Algorithm 4 receives from Algorithm 3 the schedule (e.g., Table II) indicating the time of execution of each workflow task on each resource of the service type. In lines 2-5, the algorithm sets several variables, e.g., the periods for starting up (e.g., 2) and shutting down (e.g., 1) of the resource. The variable in line 4 is the instance's billing period (e.g., 10). In line 5, this variable will check the idle time between any two consecutive tasks on each VM. The for loop in line 6 is executed for all VMs assigned during the planning phase ($vm_1^1 - vm_3^1$). Then, the for loop in line 7 is executed for all tasks on each VM (e.g., t_2, t_5 and t_8 on vm_1^1). Since no VM is provisioned at the beginning of the workflow execution, the delay in booting the VM cannot be avoided (lines 8-14).

However, the other tasks ($t_4 - t_9$) that start at a time greater than the booting delay can start executing and thus avoid the VM booting delay. The algorithm provisions VMs (vm_{start}) in advance of the tasks' start times (line 9), taking into account the VM provisioning delay ($vm_{billingPeriod}$). Finally, if a VM has subtracted the shutdown delay time from the VM idle time (line 16) and the difference is greater than or equal to the instance's billing period (line 16), the VM is terminated immediately after the output data is transferred to the VMs of its successors (lines 15-19).

Furthermore, if no more tasks are running on a VM, the VM is also terminated immediately after the output data has been transferred to the VMs of its successors (lines 22-24). The makespan for the workflow with the selected VMs ($vm_1^1 - vm_3^1$) is 30 seconds. Taking into account the data transfer time and the delay times for booting and shutting down the VM instances, the total cost of the sample workflow is 18.

TABLE II. THE SCHEDULING OF THE WORKFLOW TASKS FOR EACH STEP OF EXECUTING DSAWS ON THE SAMPLE WORKFLOW OF FIG. 2

Step	Task	Rank	Current Sim Time	timeLine	$\frac{t_{rank}}{vm_j^{speed}}$	VM selection	Start	End	VM cycle
1	t_2	32	2	32	32	vm_1^1	2	6	1
1	t_1	31	2	32	31	vm_2^1	2	7	1
1	t_3	30	2	32	30	vm_3^1	2	8	1
2	t_5	25	6	28	25	vm_1^1	6	15	2
3	t_4	25	7	27	25	vm_2^1	7	15	2
4	t_6	20	8	26	20	vm_3^1	8	13	2
5	t_9	14	13	21	14	vm_3^1	13	27	3
6	t_8	12	15	19	12	vm_1^1	15	29	3
6	t_7	10	15	19	10	vm_2^1	15	25	3

TABLE III. THE CHARACTERISTICS VALUES FOR EACH WORKFLOW APPLICATION

Workflow type	Number of levels	Number of tasks	Number of dependencies	Mean runtime (sec.)	Mean data size (MB)
Montage	9	1000	4485	11.37	3.21
CyberShake	5	1000	3988	22.75	102.29
LIGO	6	1000	3246	227.7	8.9
Epigenomics	8	997	3228	3866.4	388.59

IV. EVALUATION

Our experiment evaluated DSAWS with other competitive algorithms like CGA and Dyna for scheduling the selected scientific workflow applications. The experiment was conducted in the DISSECT-CF-WMS [27] simulator, which is an extension of the DISSECT-CF simulator. It is useful for running scientific workflows on cloud resources. DISSECT-CF-WMS focuses on the user-side behaviour of clouds, while DISSECT-CF focuses on the internal behaviour of IaaS systems. It also supports dynamic provisioning to meet the resource requirements of the workflow application while running on the infrastructure, taking into account the provisioning and de-provisioning delays of a cloud-based VM.

We used a library of realistic workflows introduced by Bharathi et al. [28] to evaluate our scheduling algorithm. We evaluate our algorithm by simulating it with synthetic workflows based on real scientific workflows with different structures. We selected four realistic workflows from different scientific applications, which are Montage from the field of astronomy, CyberShake from the field of earthquake science, Inspiral (LIGO) from the field of gravitational physics, and Epigenomics from the field of biology. Fig. 3 shows the structure of each workflow. All relevant characteristic values required for the above algorithms are listed in Table III for the analysis of experiments. We have used these values to obtain the rank values and assign the corresponding VM to each task. The performance of the four workflows in DSWAS is compared with Dyna and CGA approaches.

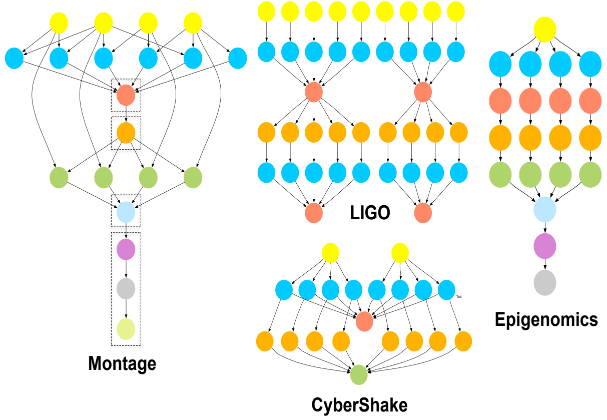

Fig. 3. The structure of the Montage, CyberShake, LIGO and Epigenomics workflows [28].

TABLE IV. TYPES OF VM BASED ON GOOGLE COMPUTE ENGINE OFFERING

Name	Memory (GB)	Google compute engine units	Price per minute($)
n1-standard-1	3.75	2.75	0.00105
n1-standard-2	7.5	5.5	0.0021
n1-standard-4	15	11	0.0042
n1-standard-8	30	22	0.0084
n1-standard-16	60	44	0.0168
n1-standard-32	120	88	0.0336
n1-standard-64	240	176	0.0672

We created a model of the cloud infrastructure of Google Cloud Engine[1] with different VM configurations selected from the predefined machine types of the cloud. An IaaS provider with a single data region and seven types of VMs was set up. Table IV shows the VM setup type based on Google Compute Engine offerings. For Google Cloud Engine, the core of Compute Engine CPU provides a minimum processing capacity of 2.75 GCEUs (2.75 ECUs), or about 2750 MIPS [29]. A billing slot of 60 seconds was modelled, as service providers such as Google Compute Engine and Microsoft Azure offered. Provisioning delay was set to 30 seconds [31] and de-provisioning delay to three seconds [25] for all types of VMs. The bandwidth between VMs was set to 1 Gbit.

To evaluate the ability of each approach to achieve a valid solution that meets the deadlines, we set the success rate metric, which is calculated as the proportion of the current execution times to the given deadlines. For the evaluation, we set three deadline factors based on the maximum rank value of each workflow. The maximum rank value represents the strict deadline factor (1), as shown in Table V. In addition, the moderate and relaxed deadlines are obtained by multiplying the maximum rank values by (1.5) and (2), respectively.

Fig. 4, 6, 8, and 10 show the results of the success ratios for each workflow with the three algorithms. On the other hand,

[1] https://cloud.google.com/compute/all-pricing

TABLE V. THE MAXIMUM RANK VALUES IN SECONDS FOR EACH SCIENTIFIC WORKFLOW

Workflow type	The maximum rank value (strict Deadline factor)
Montage	369 seconds
CyberShake	736 seconds
LIGO	625 seconds
Epigenomics	27232 seconds

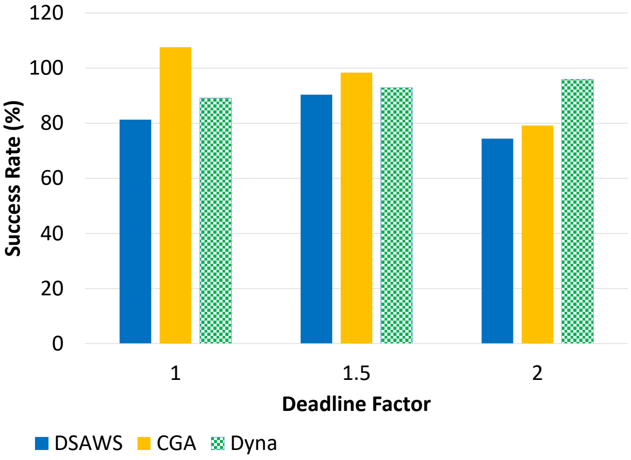

Fig. 4. The makespan of the three algorithms with the montage application.

Fig. 5, 7, 9, and 11 show the execution costs (in $) for each workflow with the same algorithms.

In the case of Montage workflow, all algorithms completed the execution of the workflow within the deadline, except CGA, with the strict deadline factor, as shown in Fig. 4. Dyna met all deadline factors, as shown in Fig. 4. The DSAWS approach met all deadlines with the lowest cost compared to the other algorithms, as seen in Fig. 5. The Montage workflow has many parallel tasks with a short execution time in the second level. This drastically increases the overall cost of the workflow as more resources are consumed by Dyna, as shown in Fig. 5. However, DSWAS overcomes this disadvantage by using the leftover time of resources to save costs. Furthermore, Montage has nine levels and six of these levels are controlled by the single-thread jobs with a total execution time of 332 seconds. Levels 3 and 4 have 142 seconds, which is more than two instance cycles, with the billing period being 60 seconds. Levels 6-9 have 190 seconds, which is equivalent to three instance cycles. Therefore, the DSAWS algorithm keeps only one VM during these periods to reduce the execution cost and meet the deadline.

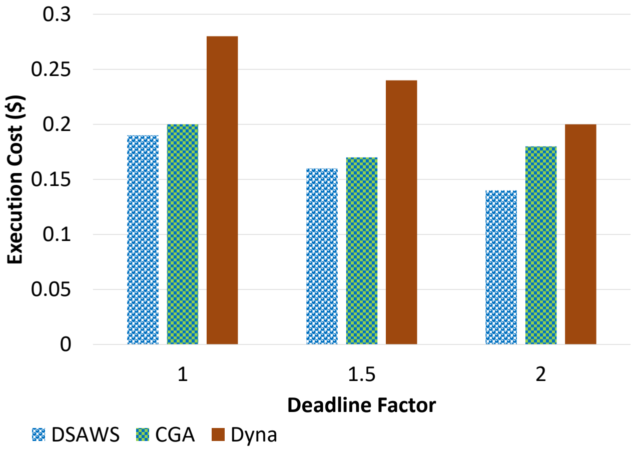

Fig. 5. The execution cost of the three algorithms with the montage application.

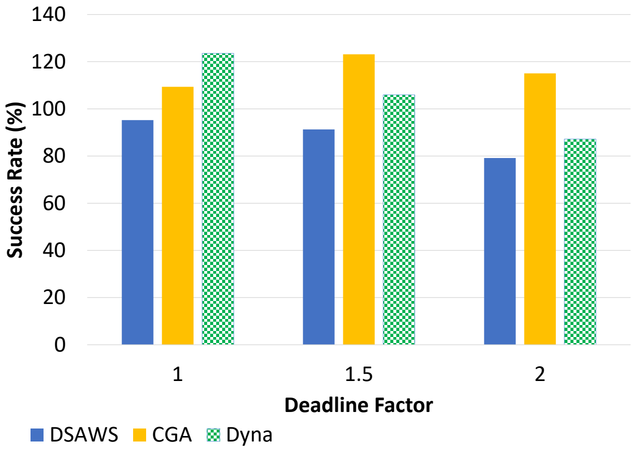

Fig. 6. The makespan of the three algorithms with the CyberShake application.

In the case of the CyberShake workflow, which has a data transfer bottleneck for most scheduling algorithms. This drawback is eliminated by the DSAWS described in this paper, which allocates resources to all tasks based on their rank value. It guarantees that all tasks are completed within the deadline and starts new instances only when needed. Therefore, DSAWS reduces data transfer by assigning tasks to the same set of resources. The CGA scheduler could not meet the deadline for all deadline factors successfully. While Dyna met the relaxed deadline factor, it failed to meet the other deadline factors. DSAWS, on the other hand, meet all deadlines with the lowest execution cost, as shown in Fig. 6 and Fig. 7, respectively. CyberShake has five levels, with most tasks at levels 2 and 3 totalling 994 tasks out of 1000. This results in high concurrency and a large amount of data transfers. CyberShake is a compute- and data-intensive workflow. In addition, level two has 497 tasks with 95.35% of the total execution time of the workflow tasks. As a result, the Dyna and CGA algorithms launched many instances of the computation service, and this has led to an increase in the makespan and execution cost of the workflow due to the increase in data transfers between resources.

In LIGO, DSAWS successfully met all deadline factors, while CGA failed to meet all deadline factors. Dyna met the relaxed deadline factor but failed to meet the other deadline factors, as shown in Fig. 8. CGA and Dyna perform badly because fewer resources are available for tasks with long execution times. LIGO is a data and CPU-intensive workflow, and this slowed down the execution of the workflow significantly. However, the proposed technique analyses the workflow structure, determines the number of tasks at each level and provides a rank value for all workflow tasks. The algorithm then assigns the appropriate type of resources to these tasks

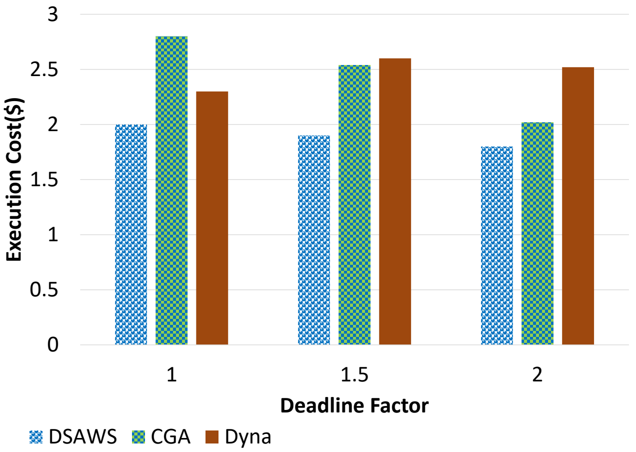

Fig. 7. The execution cost of the three algorithms with the CyberShake application.

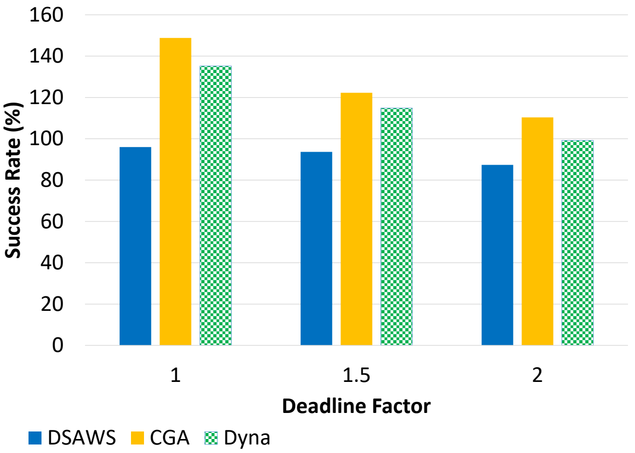

Fig. 8. The makespan of the three algorithms with the LIGO application.

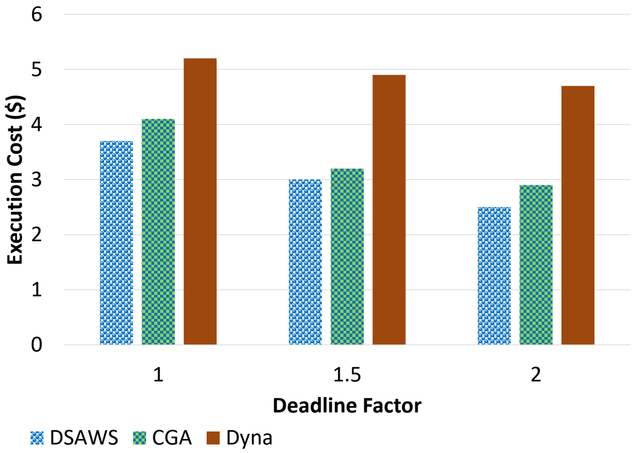

Fig. 9. The execution cost of the three algorithms with the LIGO application.

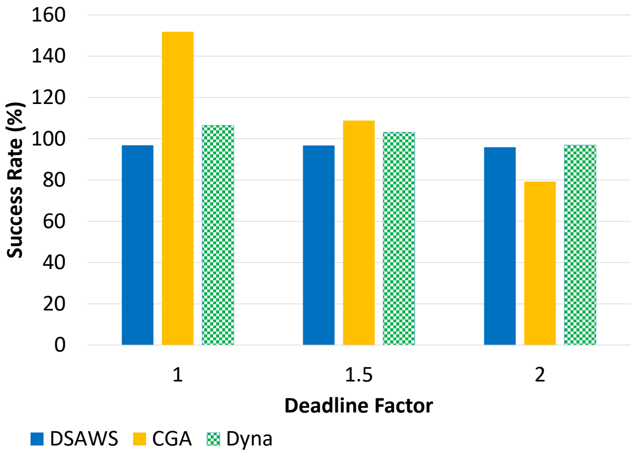

Fig. 10. The makespan of the three algorithms with the Epigenomics application.

in the workflow and executes them to meet the user-specified deadline, as shown in Fig. 8. Also, unlike the other algorithms, DSAWS achieved the cheapest cost among all schedules, as shown in Fig. 9. LIGO has 483 tasks with runtimes greater than the mean execution time (e.g. 227.7). The time difference between tasks can be up to 3 $times$ the mean runtime of the workflow tasks. This results in idle time for other resources and gaps in scheduling between workflow tasks in the case of CGA and Dyna.

In the case of the Epigenomics workflow, the CGA scheduler did not successfully meet the deadline for the strict and moderate deadline factors, but it was able to meet the relaxed deadline factor. Similarly, Dyna has met the relaxed deadline factor but failed to meet the moderate and strict deadline factors. For some Epigenomics tasks, there are significant differences in execution times of 15000 $times$ or even more. Therefore, the CPU performance reduction will significantly impact the processing time of these tasks and lead to delays for CGA and Dyna. The DSAWS algorithm, on the other hand, met all deadlines, as shown in Fig. 10. Furthermore, unlike the other two algorithms, DSAWS has the lowest execution cost, as shown in Fig. 11. This pattern is repeated in Epigenomics experiments, but the time difference can be up to 7 $times$ of the average runtime of the workflow tasks (e.g. 3866.4). Epigenomics has eight levels, with most tasks at level 5 comprising 245 tasks and 99.8% of the total workflow execution time. These differences show that there is a significant need for resources at this level of the workflow for CGA and Dyna.

Finally, the DSAWS algorithm met all the deadline factors of each workflow, while the CGA and Dyna approaches met 25% and 50% of all the deadline factors of all workflows, respectively. These results are consistent with what was expected for each algorithm. The static heuristic (e.g., CGA) was not more successful in meeting deadlines, but the adaptability of Dyna allows it to meet its aim more frequently. The experiment's results also show the efficiency of DSAWS in terms of its ability to produce more cost-effective schedules. DSAWS outperformed all other algorithms we compared it with in all situations. DSAWS succeeds at the lowest cost compared to CGA and Dyna algorithms, regardless of whether the deadline was met or not. Moreover, CGA showcases its ability to generate more cost-effective schedules and surpasses Dyna about 92% regardless of whether the deadline was met or not. For some structures (e.g., CyberShake and Epigenomics),

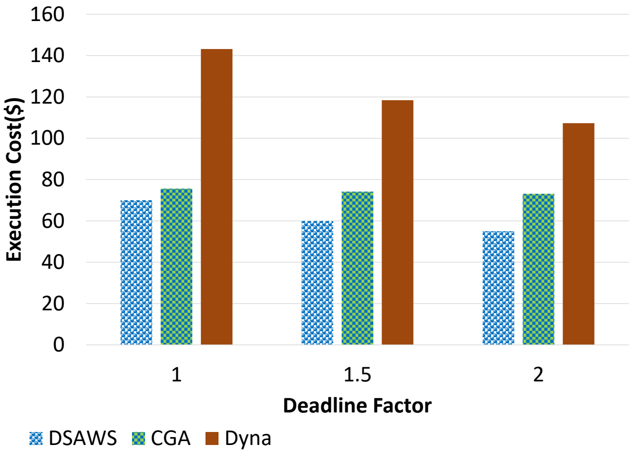

Fig. 11. The execution cost of the three algorithms with the Epigenomics application.

our proposed algorithm uses the initial leased VMs to schedule all tasks of the same workflow to minimise data transfer costs. Other structures (e.g., Montage and LIGO) have many tasks with a short execution time, and many instances of the computation service are launched while only a small part of their time interval is used. Therefore, the proposed algorithm uses the remaining time in the current billing period of the VMs to avoid wasting resources. An additional feature of DSAWS evident in the results is its ability to increase the time required to execute the workflow incrementally. The significance of these relationships is that many users are willing to trade off execution time for lower costs, while others are willing to pay higher costs for faster execution. The algorithm must behave within this logic so that the deadline number is perceived as fair by the users.

V. Conclusion and Future Works

When scheduling workflows in the cloud, resource allocation is important. A good resource estimation method helps the user to reduce the cost and time of workflow execution. Numerous algorithms face the challenge of meeting the user's deadline requirements while minimising the cost of running the workflow. The DSAWS scheduler presented in this paper analyses the structure of the incoming workflow and assigns an optimal resource provisioning mechanism based on the deadline constraint and the rank values of the tasks in the workflow. The main implementation of this algorithm is to make the second phase follow the schedule of the first phase (scheduling of workflow tasks on selected resources). We evaluate the performance of our algorithm by simulating it with four synthetic workflows based on real scientific workflows with different structures. For some structures (e.g., CyberShake and Epigenomics), our proposed algorithm uses the initial leased VMs to schedule all tasks of the same workflow to minimise data transfer costs. Other structures (e.g., Montage and LIGO) have many tasks with a short execution time, and many instances of the computation service are launched while only a small part of their time interval is used. Therefore, the proposed algorithm uses the remaining time in the current billing period of the VMs to avoid wasting resources. The proposed algorithm reduces the overall execution cost of a workflow while achieving a deadline set by the user. Experimental results show that DSAWS outperforms the Dyna and CGA algorithms in terms of meeting workflow deadlines while reducing execution costs. DSAWS met all the deadline factors of each workflow, while CGA and Dyna met 25% and 50%, respectively, of all the deadline factors of all workflows.

In the future, we plan to improve our algorithm to consider the user's deadline and other Quality of Service (QoS) objectives, such as resource utilisation and energy consumption, simultaneously.

Conflict of Interest: The authors declare that they have no conflict of interest.

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Prominent Security Vulnerabilities in Cloud Computing

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***Abstract*—This research study examines the significant security vulnerabilities and threats in cloud computing, analyzes their potential consequences for enterprises, and proposes effective solutions for mitigating these vulnerabilities. This paper discusses the increasing significance of cloud security in a time characterized by rapid data expansion and technological progress. The paper examines prevalent vulnerabilities in cloud computing, including cloud misconfigurations, data leakage, shared technology threats, and insider threats. It emphasizes the necessity of adopting a proactive and comprehensive approach to ensure cloud security. The report places significant emphasis on the shared responsibility paradigm, adherence to industry laws, and the dynamic nature of cybersecurity threats. The situation necessitates the cooperation of researchers, cybersecurity professionals, and enterprises to proactively address these difficulties. This partnership aims to provide a thorough manual for organizations aiming to bolster their cloud security measures and safeguard valuable data in an ever-evolving digital landscape.**

***Keywords*—Cloud computing; vulnerabilities; cloud security; cloud misconfigurations; data loss; threats**

I. Introduction

Cloud computing has revolutionized how companies manage data and information technology, offering flexible, on-demand resources that facilitate innovation and collaboration. Through services such as Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS), businesses of all sizes can now optimize costs, improve agility, and enhance efficiency. Despite its numerous benefits, cloud computing is not without its challenges, particularly in the realm of security. misconfigurations, improper authentication, and phishing attempts are among the many vulnerabilities that have led to significant data breaches and financial losses for organizations [1]. The financial implications of these security vulnerabilities are stark, with the average cost of a data breach reaching $4.24 million in 2023, the highest in 17 years, according to the International Business Machines (IBM) Corporation. Moreover, breaches in cloud environments have proven to be more costly than traditional on-premises intrusions, underscoring the critical need for robust cloud security measures. This study aims to examine the impact of cloud computing vulnerabilities on organizations and review practical mitigation strategies to enhance cloud security. It seeks to explore the advantages and disadvantages of these solutions, considering security and usability trade-offs. The ultimate goal is to contribute to the cloud security literature and provide insights for practitioners and policymakers on safeguarding valuable data in an increasingly digital world.

The rest of the paper is organized as follows: Section II discusses the selection of papers through the PRISMA methodology, followed by a detailed literature review of related works in Section II. Section III presents cloud computing statistics, highlighting its growth and the paradigm shift in organizations. The methodology, including penetration testing and vulnerability scanning, is outlined in Section IV. The paper concludes with a discussion on future trends and a summary of the findings and recommendations in Section V.

II. Literature Review

A. Selection of Papers by PRISMA

This paper aims to conduct a rigorous Systematic Literature Review (SLR) of the existing literature on prominent security vulnerabilities in cloud computing, guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. PRISMA's transparent, methodological approach ensures an unbiased selection and assessment of the papers, enabling a comprehensive and replicable review. In the first step, the search was conducted in the IEEE Xplore and Google Scholar databases using the querying combination of the following keywords: (Security Vulnerabilities OR Threats) AND Cloud Computing. The literature is restricted to studies published between 2012 and 2023 in English. Google Scholar revealed 8580 papers that discuss security vulnerabilities in cloud computing, specifically focusing on data breaches, unauthorized access, and other security threats. These 8,580 search papers were registered, with 2,000 duplicate papers removed before screening and 4,080 papers excluded for other reasons. Additionally, 29 papers were identified in the IEEE Xplore. Thirteen papers were excluded after screening the title and abstract due to unspecific goals. A total of 157 and 9 papers were assessed for eligibility from the Google Scholar and IEEE Xplore databases, respectively. Finally, after a thorough review and study of these papers, 44 papers were selected from the Google Scholar database and 7 from the IEEE Xplore, making a total of 51 papers selected. This selection process of papers, as conducted by PRISMA, is illustrated in Fig. 1.

B. Related Papers

Cloud computing has a significant role in modern business and individuals' lives. Numerous articles and studies are focused on different literary studies in this field. For instance, a review article written by Alouffi et al. [2] titled "A Systematic Literature Review on Cloud Computing Security: Threats and Mitigation Strategies" identified seven major security threats to cloud computing services, including data tampering and leakage, intrusion of data, and storage of data. Similarly, the paper identifies blockchain as a partnering technology to address some of the security concerns. Akello et al. in [3] summarized existing security surveys in the domains of cloud, fog, and edge computing. The paper underscores the need for

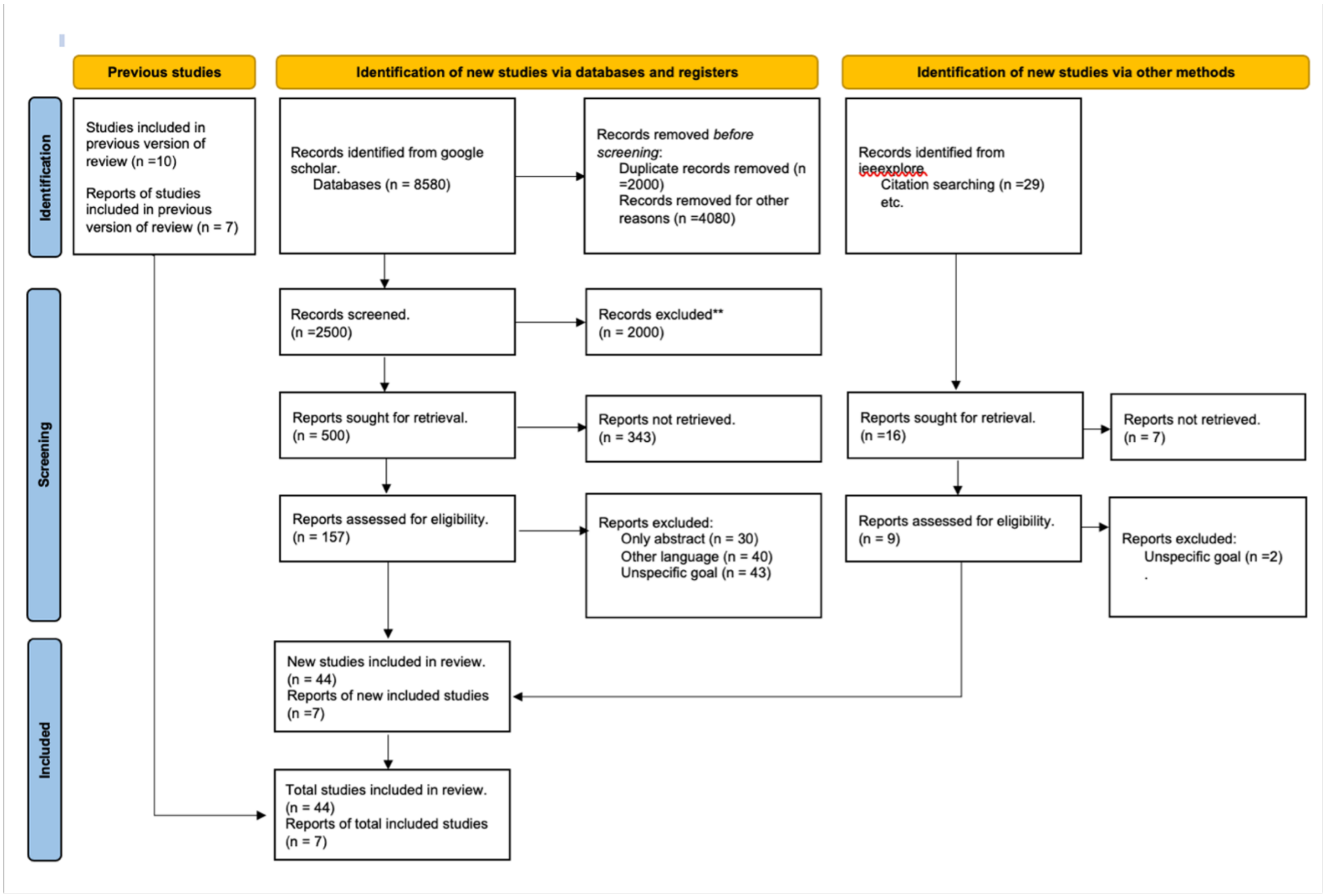
Previous studies
Identification of new studies via databases and registers
Identification of new studies via other methods
Identification
Screening
Included
Studies included in previous version of review (n =10)
Reports of studies included in previous version of review (n = 7)
Records identified from google scholar.
Databases (n = 8580)
Records removed before screening:
Duplicate records removed (n =2000)
Records removed for other reasons (n =4080)
Records identified from ieeexplore
Citation searching (n =29)
etc.
Records screened.
(n =2500)
Records excluded**
(n = 2000)
Reports sought for retrieval.
(n = 500)
Reports not retrieved.
(n = 343)
Reports sought for retrieval.
(n =16)
Reports not retrieved.
(n = 7)
Reports assessed for eligibility.
(n = 157)
Reports excluded:
Only abstract (n = 30)
Other language (n = 40)
Unspecific goal (n = 43)
Reports assessed for eligibility.
(n = 9)
Reports excluded:
Unspecific goal (n =2)
New studies included in review.
(n = 44)
Reports of new included studies
(n =7)
Total studies included in review.
(n = 44)
Reports of total included studies
(n = 7)

Fig. 1. Selection of papers for literature review using PRISMA.

addressing security problems related to these domains while carrying out a comprehensive examination of the different security problems associated with them.

Humayun et al. in [4] in their review paper titled "Cyber Security Threats and Vulnerabilities: A Systematic Mapping Study" included a list of existing studies relating to cyber security vulnerabilities and categorizes them considering the type of a commonly known security threat vulnerability, victim of a cyber threat, vulnerability degree, and method of data collection as well as verification. Another review paper in [5] titled "Security Issues in Cloud Computing: A Review on Security Problems in Cloud Computing—A Survey" also indicated security hurdles like data confidentiality, data integrity, and data privacy.

Numerous other articles exist [6], [5] that offer a comprehensive examination of the diverse security concerns within the realm of cloud computing. These scholarly articles delineate a number of security challenges, including but not limited to issues pertaining to data privacy, data confidentiality, and data integrity. It is imperative to acknowledge that although these articles offer a comprehensive examination of the diverse security concerns in cloud computing, they do not encompass all possible aspects. However, these resources provide a valuable foundation for individuals seeking to further their knowledge on this subject matter. The articles are summarized in the table below:

III. Cloud Computing Statistics

Scalability, flexibility, and cost-efficiency are among the benefits of cloud computing, which is continually growing. However, cloud computing presents severe security issues. Research shows that 90% of cloud data is unstructured and requires different processing and storage methods. This exponential increase is a major issue. Text, photos, audio, video, and other unstructured data have no standard or schema. Unstructured data is harder to manage and secure than structured data. Multi-cloud strategies are growing, with an estimated 87% of companies going multi-cloud by 2024. Multi-cloud setups do, however, also raise the complexity and risk of security breaches, which in 2022 accounted for 45% of all data breaches. The confidentiality, integrity, and availability of cloud data and infrastructure can be jeopardized by security breaches, which can lead to monetary losses, damages to one's reputation, legal ramifications, and regulatory fines. The average cost of these breaches globally was $4.35 million in 2022, and the healthcare industry faced costs as high as $10.10 million. The financial consequences are enormous. In addition, there was a 38% increase in cybersecurity threats between

TABLE I. SUMMARY OF LITERATURE REVIEW PAPERS

Author	Year	Description	Type of Paper
Prabadevi et al. [1]	2014	The paper reviews the list of existing studies relating to cybersecurity vulnerabilities and categorizes them considering the type of a commonly known security threat vulnerability, victim of a cyber threat, vulnerability degree, and method of data collection as well as verification. The authors suggested state-of-the-art techniques for recognizing human emotions from speech, facial expressions, and multimodal signals to address security issues.	Literature Review
Akello et al. [3]	2022	Provides a summary of security surveys in the cloud, fog, and edge computing domains.	Literature Review
Alouffi et al. [2]	2021	The research revealed seven primary security vulnerabilities that pose a risk to cloud computing services. These vulnerabilities include data manipulation and leakage, intrusion, and storage. The study also proposes the utilization of blockchain as a complementary solution to address security concerns.	Literature Review
Humayun et al. [4]	2020	identify available studies on cybersecurity vulnerabilities and categorize these solutions against commonly available security vulnerabilities, victims of cyber threats, vulnerability severity, and data collection and validation methods.	Mapping Study
Patel et al. [7]	2020	The paper overviews cloud security issues, threats, and related attacks.	Literature Review
Kumar et al. [6]	2017	Provide an overview of cloud computing security issues. The paper identifies several security challenges, such as data privacy, confidentiality, and integrity.	Survey
Tabrizchi et al. [8]	2020	Identify several security challenges such as data privacy, confidentiality, and integrity.	Survey
Shaikh et al. [5]	2012	Provides an overview of the various security issues in cloud computing. The paper identifies several security challenges, such as data privacy, confidentiality, and integrity.	Survey
Sharma et al. [9]	2021	The paper proposes a new topology for a single-phase inverter that can reduce the leakage current and increase the efficiency of photovoltaic systems.	Literature Review
Jabir et al. [10]	2016	Th paper presents a framework for conducting penetration testing on a private cloud computing infrastructure.	Research
Shetty et al. [11]	2012	Analyzes the security level of network applications on routers between cloud subscribers and cloud providers.	Research
Kumar et al. [12]	2019	A comprehensive survey focusing on cloud security requirements, threats, vulnerabilities, and countermeasures. It provides an in-depth analysis of cloud computing security challenges and offers a unified taxonomy for security in the cloud environment.	Survey
Sun et al. [13]	2020	This paper analyzes security and privacy protection in cloud computing. It reviews various privacy security issues, access control technologies, and attribute-based encryption (ABE) for cloud security. The paper also explores searchable encryption techniques and integrating various technologies for enhanced privacy and security in cloud computing.	Review
Stergiou et al. [14]	2018	This paper addresses security, privacy, and efficiency in sustainable cloud computing, particularly Big Data and IoT. It explores the integration of cloud computing with IoT technologies and the resulting security challenges while proposing a new system to improve cloud computing security through enhanced network architecture and encryption methods.	Review
Parikh et al. [15]	2019	The paper critically analyzes the unique security and privacy challenges in cloud, fog, and edge computing environments. It discusses the emerging security risks and privacy concerns in these distributed computing models, especially in relation to IoT integration and increasing data traffic. The study also proposes strategic approaches to mitigate these challenges, emphasizing the need for robust security mechanisms tailored to the complexities of interconnected computing systems.	Review
Ahmed et al. [16]	2016	This paper presents a detailed taxonomy for identifying security issues in cloud computing environments. It systematically categorizes various security threats and challenges in cloud computing, offering a structured framework for understanding and addressing these issues. The paper emphasizes the need for comprehensive security strategies to manage cloud security risks' evolving and complex nature.	Taxonomy Review
Guan et al. [17]	2018	The paper explores data security and privacy challenges in fog computing. It critically discusses the unique security and privacy issues that arise due to the nature of fog computing as an extension of cloud computing, especially with regard to IoT applications. The study highlights the need for innovative security approaches due to the limitations of existing cloud computing security solutions in the fog computing paradigm.	Review

2022 and 2023, underscoring the critical need for stronger security protocols to keep bad actors away from cloud data and infrastructure[1]. Phishing, ransomware, Denial-of-Service (DoS), Distributed Denial-of-Service (DDoS), malware, insider threats, and others are cybersecurity attacks. These attacks exploit cloud computing weaknesses such as misconfiguration, inadequate authentication, a lack of encryption, insufficient monitoring, and shared responsibility. Thus, organizations must take a holistic and proactive approach to cloud security that covers data protection, access control, encryption, identity management, threat detection, incident response, compliance management, and more. Some of the aspects under the problem statement are discussed in detail below:

A. Exponential Growth

The use of cloud services by numerous industries and sectors adds to the exponential expansion of cloud data. According to the International Data Corporation (IDC), global public cloud services and infrastructure investment expanded from $229 billion in 2019 to $500 billion in 2023, a 22.3% compound annual growth rate (CAGR). More companies are

[1] https://aag-it.com/the-latest-cyber-crime-statistics/

moving their data and apps to the cloud to maximize its scalability, flexibility, and cost-effectiveness [12]. However, more data is generated, processed, and stored in the cloud, presenting new data management and security challenges. Cloud data grows exponentially due to new technologies and trends that generate large amounts of data. The Internet of Things (IoT) is a network of internet-connected devices that collect and exchange data. Cisco predicted that global IoT connections would rise from 18.4 billion in 2018 to 43.9 billion in 2023, a 19% CAGR. It was also predicted that global IoT data traffic would expand from 14.4 exabytes per month in 2018 to 79.4 by 2023, a 41% CAGR. Since IoT devices have limited storage and processing, most data would be saved and analyzed in the cloud. Another reason driving exponential data expansion in cloud systems is the demand for data analytics and Artificial Intelligence (AI) applications. Organizations can improve customer experiences, processes, and insights with data analytics and AI [12]. The global business intelligence and analytics software market was estimated to expand from $23.1 billion in 2020 to $33.8 billion in 2025, a 7.9% CAGR, according to Gartner. The worldwide AI software market was to expand 33.2% from $22.6 billion in 2020 to $126.0 billion in 2025 [23]. Cloud storage and processing of enormous volumes of data are needed to train and execute these applications. According to IDC's prediction, there is an anticipated CAGR of 12.9% in spending on cloud infrastructure during the period of 2021–2026. This growth is expected to result in a total expenditure of $135.1 billion in 2026, representing 67.3% of the total expenditure on compute and storage infrastructure. The utilization of shared cloud infrastructure is projected to represent 72.3% of the overall cloud capacity, exhibiting a CAGR of 13.8%[2]. The expenditure on specialized cloud infrastructure is projected to see a CAGR of 10.7%, reaching a total of $37.4 billion. Expenditure on non-cloud infrastructure is projected to exhibit a CAGR of 2.3%, ultimately attaining a value of $65.6 billion by the year 2026. It is projected that expenditures made by service providers on compute and storage infrastructure would see a CAGR of 12.1%, ultimately reaching a total of $131.9 billion by the year 2026[3]https://infotechlead.com/cloud/cloud-spending-to-grow-17-to-88-9-bn-in-2022-vs-10-in-2021-idc-74765. This is shown in the graph below.

The global market for AI had a valuation of USD 454.12 billion in 2022 and is projected to reach approximately USD 2,575.16 billion by 2032, exhibiting a CAGR of 19% from 2023 to 2032, as shown below.

B. Paradigm Shift in Organizations

Cloud computing is a multifaceted phenomenon that encompasses both technological advancements and strategic considerations, exerting influence over various aspects of an organization, such as its structure, culture, and performance. Organizations that implement cloud computing can experience several advantages, including enhanced agility, innovation, and collaboration, with decreased operational expenses and complexity. Nevertheless, these organizations also have other obstacles, including the need to adapt to evolving roles and duties, effectively oversee numerous vendors and platforms, and guarantee the protection and confidentiality of data. The shared responsibility model is a fundamental component of cloud security, defining the allocation of security responsibilities between the cloud service provider and the consumer. The level of control and responsibility that customers have over the security of their data and applications varies depending on the specific type of cloud service they are utilizing, either IaaS, PaaS, or SaaS. In the context of IaaS, it is the customer's responsibility to ensure the security of the operating system, applications, data, and network traffic[4]. Conversely, the provider assumes the responsibility of securing the physical infrastructure, virtualization layer, and network. Within the realm of SaaS, the onus of ensuring data security and user access lies solely on the customer. At the same time, the provider bears the responsibility for all other aspects.

An additional crucial element of cloud security is adherence to industry-specific legislation and standards. Examples of these include the Health Insurance Portability and Accountability Act (HIPAA) for the healthcare sector, the Payment Card Industry Data Security Standard (PCI DSS) for the payment card business, and the General Data Protection Regulation (GDPR) for data protection inside Europe. The primary objective of these regulations is to safeguard the confidentiality, integrity, and availability of sensitive data and systems. Nevertheless, these regulations enforce stringent criteria and responsibilities for both the cloud service provider and the customer. As an illustration, it is mandated under the HIPAA that both entities involved must engage in the execution of a business associate agreement (BAA), which outlines their respective obligations and duties pertaining to safeguarding protected health information (PHI)[4]. The GDPR mandates that entities must conform to the fundamental principles of data minimization, purpose limitation, and consent. Hence, enterprises must undertake a comprehensive evaluation of risks and exercise due diligence prior to the selection of a cloud service provider. The user needs to ascertain that the service provider satisfies their security and compliance prerequisites while also offering transparency and accountability in their service provisions[5]. In addition, it is imperative for organizations to consistently engage in monitoring and auditing of their cloud infrastructure in order to identify and address any possible security risks or occurrences promptly. Therefore, cloud computing represents a significant shift in the prevailing paradigm, presenting numerous advantages and posing various obstacles for enterprises. Conducting research is necessary in order to comprehensively comprehend and efficiently tackle these difficulties[6]. Organizations may effectively use the capabilities of cloud computing while mitigating potential dangers by adhering to established best practices and standards in cloud security and compliance.

C. Security Vulnerabilities

In 2022, a significant proportion of data breaches were attributed to infiltrations into cloud-based systems. This emphasizes the pressing necessity of promptly addressing the

[2] https://solutionsreview.com/data-management/80-percent-of-your-data-will-be-unstructured-in-five-years/

[3] \unskip\protect\penalty\@M\vrulewidth\z@height\z@depth\dpff

[4] https://www.crowdstrike.com/cybersecurity-101/cloud-security/cloud-vulnerabilities/

[5] https://www.cloudvulndb.org/

[6] https://www.cypressdatadefense.com/blog/cloud-computing-security-vulnerabilities/

distinct security risks that impact cloud environments. The vulnerabilities encompass a wide range of issues, including misconfigurations in cloud settings, inadequate user access controls, weaknesses in the architecture of cloud service providers, and advanced attack methodologies. Conducting research in this field is crucial for the identification of these vulnerabilities and the formulation of efficient strategies to protect sensitive data within businesses. Misconfigurations are identified as a primary contributing factor to data breaches occurring within cloud infrastructures[7]. Cloud services provide a wide range of choices, and enterprises frequently have difficulties configuring them in a secure manner. Misconfigurations have the potential to inadvertently expose data to unauthorized access, leakage, or alteration. Research can yield significant insights into prevalent misconfigurations and effective preventive measures. The infrastructure of cloud service providers represents an additional factor contributing to vulnerability. The security of data stored in cloud environments is frequently contingent upon the security measures implemented by the cloud service provider. Hence, it is vital to comprehend the prospective vulnerabilities within the provider's infrastructure and their potential impact on the data. Research also plays a crucial role in enabling enterprises to effectively monitor and stay updated on the most recent vulnerabilities. This allows them to ensure that cloud providers swiftly patch these issues. Furthermore, it is important to note that, with the continuous evolution of cyber threats, conducting research in this particular domain might provide valuable insights into emerging attack strategies and vulnerabilities that are unique to cloud computing. The acquisition of this knowledge is crucial for enterprises to adopt a proactive approach to safeguarding their data against developing dangers. Different scholars assert that it is important to enable firms to identify and address many types of attacks, including cryptojacking, denial-of-service, and server-side request forgery, within their cloud settings. It is imperative to note that the duty to ensure security in cloud computing is a collaborative effort between enterprises and cloud service providers. Gaining insight into the allocation of this responsibility and acquiring knowledge about successful collaboration are essential elements in the process of mitigating security vulnerabilities in cloud computing.

The exposed data included sensitive information such as authentication credentials, secret API data, and decryption keys. Moreover, documents contained in these servers revealed that the databases were storing data for Accenture's clients, including high-profile telecommunication companies and other Fortune 100 firms. The breach could expose Accenture and its clients to significant risks, including unauthorized data manipulation, fraud, and targeted phishing attacks. Fortunately, the exposed databases were discovered by a security researcher before any known malicious exploitation could occur. This incident underlines the critical need for stringent security practices in cloud storage configuration. The primary lesson here is the importance of regular security audits and implementing strict access controls. Companies must ensure their cloud services are correctly configured and regularly monitored for potential vulnerabilities.

The 2022 Thales Cloud Security Report by 451 Research, part of S&P Global Market Intelligence, found that 45% of businesses had a cloud-based data breach or failed audit in 2021, up 5% from 2020, raising increased concerns about cybercrime. Cloud adoption, especially multicloud usage, is rising globally. In 2021, enterprises worldwide used 110 SaaS apps, up from eight in 2015. 72% of enterprises now use multiple IaaS providers, up from 57% in 2021. One in five (20%) respondents use three or more providers, virtually doubling in 2021. Despite their growing popularity, businesses worry about the complexity of cloud services, with 51% of IT experts saying cloud privacy and data protection are harder. Complexity necessitates stronger cybersecurity. Most respondents (66%) reported that 21–60% of their sensitive data resides in the cloud. Only 25% indicated they could classify all the data. About 32% of respondents had to notify a government agency, client, partner, or employee of a breach. This should worry sensitive data-holding companies, especially in highly regulated industries. Cyberattacks continue to threaten cloud apps and data. Malware, ransomware, and phishing/whaling assaults increased for 26%, 25%, and 19% of respondents, respectively. IT professionals consider encryption essential for multicloud data protection. Most respondents use encryption (59%) and key management (52%) to secure cloud data. When asked how much of their cloud data is encrypted, just 11% replied 81–100%. Enterprises may also face key management platform sprawl. 10% utilize one to two platforms, 90% use three or more, and 17% use eight or more. Enterprises should prioritize cloud data encryption[8]. The practical usefulness of encryption platforms was shown when 40% of respondents said they avoided breach reporting because the stolen or leaked data was encrypted or tokenized. Positive signals of businesses investing in Zero Trust were also promising. About 29% of respondents are actually implementing a Zero Trust strategy, 27% are analyzing and developing one, and 23% are contemplating it. This is encouraging, but there is potential for improvement.

D. Financial Ramifications

The occurrence of data breaches inside cloud computing environments can result in major monetary losses for enterprises, impacting their immediate and sustained operational outcomes. Based on a report published by IBM, it has been determined that the worldwide mean expense associated with a data breach in the year 2023 amounted to USD 4.45 million, reflecting a 15% escalation over a span of three years[9]. Nevertheless, the financial implications of a data breach exhibit considerable disparity, contingent upon the geographical location and sector of the afflicted entity[10]. In addition to comprehending the possible financial implications associated with data breaches, it is imperative for enterprises to adopt proactive measures aimed at the prevention and mitigation of such incidents. According to a survey published by IBM, the utilization of security AI and automation has the potential to yield a reduction in the average cost of a data breach by USD 1.76 million in comparison to firms that do not employ these technologies. The implementation of security AI and

[7] https://www.upguard.com/blog/cloud-misconfiguration

[8] https://cpl.thalesgroup.com/about-us/newsroom/thales-cloud-data-breaches-2022-trends-challenges

[9] https://www.ibm.com/reports/data-breach

[10] https://newsroom.ibm.com/2023-07-24-IBM-Report-Half-of-Breached-Organizations-Unwilling-to-Increase-Security-Spend-Despite-Soaring-Breach-Costs

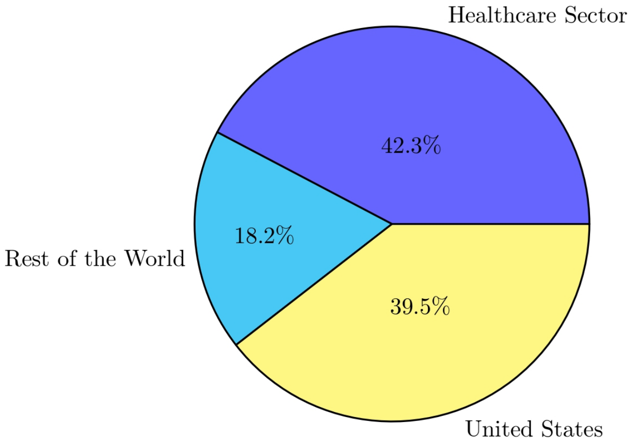

Fig. 2. The most affected sectors.

automation within businesses can contribute to the expedited identification and mitigation of potential threats, thereby reducing the adverse consequences of security breaches. In addition, it is advisable for firms to adopt comprehensive cybersecurity insurance policies, as they can provide coverage for the financial ramifications that may arise from security breaches. It is recommended that organizations allocate resources towards the implementation of cybersecurity training and awareness programs.

These initiatives aim to mitigate human errors and insider threats, which are prominent factors contributing to data breaches. By adhering to these suggestions, firms can enhance their readiness for the financial consequences associated with data breaches in cloud computing and mitigate their financial losses[11]. Data breaches can potentially lead to significant ramifications for the financial viability and long-term viability of companies as shown in Fig. 2 the healthcare sector has the lion's share of being attacked. However, these breaches can be averted and alleviated by implementing appropriate security measures and strategic investments. Conducting research in this domain can assist firms in making well-informed decisions pertaining to their cybersecurity strategy and policies.

E. Escalating Cybersecurity Attacks

The observed surge in cybersecurity attacks throughout the period spanning from 2022 to 2023 highlights the dynamic nature of the threat environment, as shown in Fig. 3. Conducting research in this domain is crucial in order to investigate the characteristics of these attacks and provide efficacious strategies to mitigate their impact. The complexity and variety of cyberattacks are increasing, incorporating a wide array of strategies like ransomware, zero-day flaws, social engineering, and supply chain attacks [18]. In recent years, there has been a notable increase in the occurrence and financial impact of ransomware attacks. Such attacks consist of an initial encryption of the victim's data before requesting a monetary ransom for the release of the hijacked information. In terms of ransomware expenditure, according to a survey by IBM in 2023, the global average expenditure was USD 5.66 million, a whopping hike of 21% from 2022. Zero-day exploits have increasingly seen their occurrence and impact. The menace this trend poses to critical infrastructure and the nation's security is substantial. These social engineering attacks are becoming more sophisticated and targeted, taking advantage of the growing use of social media and online environments. They are aimed at psychological tricks that would induce people to give out private data or engage in dangerous acts. Supply chain attacks that compromise software and hardware components from trustworthy vendors and partners pose serious challenges to firms. The assaults are capable of affecting different entities within several sectors. It is imperative for organizations to comprehend the dynamic strategies and underlying incentives driving these attacks. Research can provide valuable insights into the methods, techniques, and processes employed by cybercriminals, enabling firms to formulate proactive security plans. Research plays a crucial role in enabling companies to discern the indicators of compromise and the assault vectors employed by diverse threat actors, along with comprehending their goals and objectives.

Research can also aid firms in comprehending the behavioral and psychological elements that impact consumers' vulnerability to social engineering attacks, as well as in devising proficient awareness and education initiatives to alleviate such risks. Moreover, the proliferation of remote work and the use of cloud-based services have resulted in the expansion of the attack surface, hence heightening the susceptibility of enterprises to cyber threats. Research plays a crucial role in enabling firms to discern the precise issues presented by these transformations and formulate effective methods to safeguard remote and cloud-based operations. This encompasses the enhancement of identity and access management, the implementation of multi-factor authentication, and the improvement of threat detection and response capabilities. Research can additionally aid organizations in assessing the security stance and adherence to regulations of their cloud service providers, as well as establishing explicit roles and duties for the governance of cloud security [18]. The establishment of partnerships and cooperation among researchers, cybersecurity professionals, and other organizations is crucial to proactively addressing the increasing frequency and severity of cybersecurity threats. The dissemination of knowledge regarding emerging threats and vulnerabilities has the potential to facilitate the creation of enhanced security measures[12]. The investigation conducted in this field has the potential to make a valuable contribution to the collaborative endeavor of protecting data and systems in an ever more hostile digital environment.

F. Gap in Existing Literature

Cloud computing is a conceptual framework that presents a multitude of advantages, including scalability, elasticity, and cost-effectiveness. However, it also presents notable security obstacles. The presence of security vulnerabilities within cloud computing has the potential to jeopardize the confidentiality, integrity, and availability of both cloud services and data. This, in turn, can result in significant ramifications for both suppliers and users of cloud services. Hence, it is important to ascertain and evaluate the key security risks in cloud computing and put

[11] https://newsroom.ibm.com/2023-07-24-IBM-Report-Half-of-Breached-Organizations-Unwilling-to-Increase-Security-Spend-Despite-Soaring-Breach-Costs

[12] https://onlinedegrees.sandiego.edu/top-cyber-security-threats/

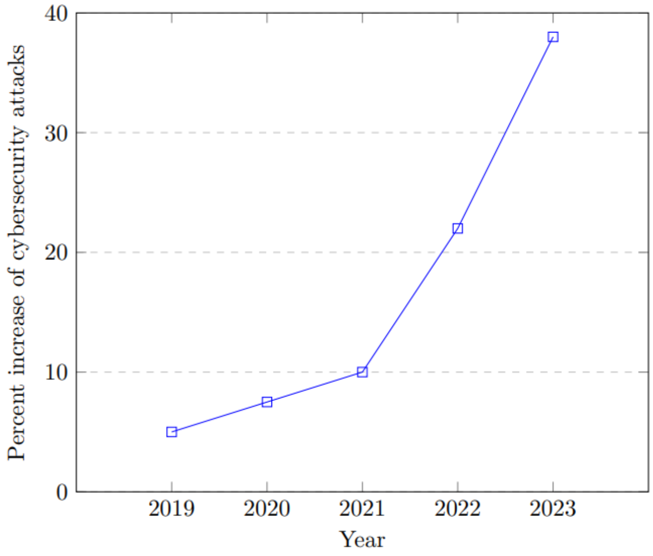

Fig. 3. Frequency increase of cybersecurity attacks between 2019 and 2023.

forth effective mitigation strategies. Nevertheless, the current body of scholarly work pertaining to cloud security is characterized by fragmentation and dispersion. It predominantly concentrates on specific aspects or domains of cloud security while lacking a comprehensive and methodical examination that encompasses the diverse security vulnerabilities, their ramifications, and the corresponding remedies within a unified and coherent analysis. The objective of this study is to address the aforementioned deficiency by undertaking a comprehensive examination of existing literature, known as a SLR, to identify and analyze the major security vulnerabilities present in cloud computing. A SLR is a methodological approach characterized by its rigorous and transparent nature that aims to locate, evaluate, and synthesize the available body of knowledge pertaining to a certain subject. This study aims to utilize the SLR approach to present a thorough and current examination of the existing research on vulnerabilities in cloud security. Additionally, it seeks to identify areas where further research is needed and suggest potential future directions in this field. This study aims to investigate the primary security issues associated with cloud computing, including questions: What are the ramifications of these security vulnerabilities for cloud service providers and their clientele? What are the productive mitigation solutions for these security vulnerabilities?

IV. Cloud Computing Security Assessment

A. *Impact of Security Vulnerabilities in Cloud Computing*

Cloud computing refers to providing various computing services, including storage, servers, databases, networking, software, analytics, and intelligence, through the Internet. Cloud computing has numerous advantages for both enterprises and individuals, encompassing scalability, cost-effectiveness, performance, reliability, and innovation. Nevertheless, the advent of cloud computing also presents novel security concerns and hazards that necessitate attention and resolution from both cloud service providers and their clientele[13]. Security vulnerabilities refer to inherent weaknesses or deficiencies inside a given system or application that can be potentially exploited by malicious actors with the intention of compromising the system's confidentiality, integrity, or availability, as well as the data it houses. Security vulnerabilities can result in significant consequences for both cloud providers and their clients[14]. These consequences include, but are not limited to, data breaches, financial losses, legal liability, reputational harm, and operational disruptions. The following are the impacts of security vulnerabilities in cloud computing:

1) Cloud misconfiguration: Cloud misconfiguration is a prevalent security vulnerability that occurs in cloud computing. Cloud misconfiguration refers to the situation in which a cloud resource or service is not appropriately configured in accordance with established security best practices or regulations. An instance may arise if a cloud storage bucket is inadvertently made accessible to the general public on the internet, hence enabling unauthorized individuals to get entry to confidential information[15].

Alternatively, a cloud user may possess an abundance of permissions or privileges that exceed the requirements of their designated position or function. Human error, a lack of knowledge base, or insufficient automation can all lead to cloud misconfiguration. Misconfigured clouds can have detrimental effects on both cloud service providers and users, including: Data breaches: Cloud misconfigurations may lead to data breaches wherein unauthorized individuals may access, steal, alter or delete confidential data stored in the cloud[16]. Data breaches can have adverse financial implications, legal obligations, government sanctions, and loss of the reputation of the customers and the cloud service providers themselves. Compliance violations: Cloud misconfiguration leads to non-compliance instances where cloud providers or clients cannot observe security standards or obligations enshrined in laws, rules, contracts, or industry frameworks. Non-compliance instances may attract fines, regulatory actions, legal proceedings or lack of confidence for cloud service providers and their customers.

Operational disruption: Cloud service/application availability and performance may be impacted by cloud misconfiguration. For example, a firewall that is not properly configured can block the lawful traffic network, and a load balancer that is not properly configured can cause the quality of service degradation. Operational disruption can cause customer dissatisfaction, reduced revenues, and diminished competitive advantage to cloud providers and their clients.

To prevent or mitigate cloud misconfiguration, cloud providers and customers should follow some best practices, such as:

a) Enforce the principle of least privilege: The principle of least privilege suggests that each user or service should possess only the essential level of access or permissions necessary to carry out their designated tasks. The use of this measure

[13] https://www.wiz.io/academy/common-cloud-vulnerabilities

[14] https://www.orientsoftware.com/blog/vulnerability-in-cloud-computing/

[15] https://www.trendmicro.com/vinfo/us/security/news/virtualization-and-cloud/the-most-common-cloud-misconfigurations-that-could-lead-to-security-breaches

[16] https://www.techtarget.com/searchsecurity/definition/data-breach

can effectively decrease the attack surface and mitigate the potential extent of harm in the event of a security breach.

b) Use third-party tools: Third-party technologies can scan and identify instances of cloud misconfiguration, as well as offer advice or remedial measures. One illustration of how a cloud-native application protection platform (CNAPP) might enhance the visibility and security of cloud resources can be observed.

c) Review and audit regularly: Regular evaluation and auditing of cloud configurations by both cloud providers and clients is critical to ensuring adherence to security policies and best practices. In addition, it is essential for individuals to diligently oversee and record any modifications or actions pertaining to their cloud-based assets, with the purpose of identifying any irregularities or occurrences.

2) Data leakage: Data leakage is a prevalent security risk that is frequently seen in the realm of cloud computing. Data leakage is the unintended or purposeful transfer of data from a secure source to an unauthorized destination[17]. Unencrypted communication lines, unsecured APIs, employees with ill-intent within the organization, hacked passwords, third party dependencies may be potential data leakage avenues.

Data leakage is a serious threat for cloud service providers and their clients. These risks involve data breaches, which can lead to monetary losses, legal issues, fines, and damage to one's reputation. Also, it is worth mentioning that privacy breaches occur when the personal or confidential data is divulged without the due authority, therefore leading to identity theft, fraud, or harassment. Lastly, an unregulated data leakage is also capable of destroying a company's competitive advantage by revealing sensitive information such as secret knowledge, business strategies, or important assets to competitors. It is important to follow the current best practices in order to prevent or mitigate these risks. This involves putting up several security measures to make sure that the data is not accessed by individuals without authority to do so. These measures include encrypting data both when it is stored and when it is being transmitted, using secure application programming interfaces (APIs) that comply with recognized security standards, and deploying data loss prevention (DLP) solutions to identify, categorize, and safeguard sensitive data. Additionally, access and usage policies are enforced across both cloud-based and on-premise environments.

3) Shared technology vulnerabilities: The presence of shared technology vulnerabilities in cloud computing arises from the fundamental utilization of common infrastructure, platforms, and software for the provision of services to numerous consumers. Consequently, any flaw present in the shared technology possesses the capacity to pose a possible threat to all users. These vulnerabilities have the potential to result in data breaches, which can expose sensitive information and result in financial losses, legal consequences, and reputational damage for both service providers and customers.

Furthermore, these entities have the potential to interfere with many services, exemplified by their involvement in denial-of-service assaults, resulting in the deterioration or complete cessation of these services. Resource abuse is a significant worry in the realm of cybersecurity since malevolent actors exploit communal technology for illicit objectives, resulting in escalated expenses, diminished operational efficiency, and compromised availability [19]. In order to address these risks, it is imperative for both cloud providers and clients to adhere to established best practices. These include timely patching and update, resource isolation, segregation. Also, constant tracking and auditing should ensure prompt detection of irregularities or any breach in the security.

4) Insecure interfaces and APIs: Cloud computing security is a great problem due to insecure interfaces and APIs. The communication and interaction between the services are done through these interfaces and APIs, but if the interfaces or the APIs are poorly designed and also not secured, then they can be the biggest dangers that a system may have. They could arise through weaknesses in authentication, inappropriate encryption, ineffective input validation, and poor error handling [18]. The potential outcomes of these vulnerabilities might have significant ramifications, such as instances of data breaches where confidential data may be illicitly accessed, pilfered, altered, or erased. This can lead to financial detriments, legal implications, regulatory penalties, and reputational harm for both cloud service providers and their clientele[19]. Furthermore, service disruptions like DDoS attacks can have an impact on the availability and performance of cloud services and apps.

In summary, the exponential expansion of cloud computing has undeniably revolutionized the manner in which enterprises manage their data and information technology requirements, presenting a multitude of benefits in relation to adaptability, availability, and cooperation. Nevertheless, this paradigm shift has concurrently presented a plethora of security concerns and vulnerabilities that necessitate resolution in order to safeguard confidential information and uphold the authenticity of cloud infrastructure.

B. Cloud Security Assessment Techniques

1) Penetration testing: Penetration testing is a technique employed to assess the security of a cloud environment by emulating an attack originating from a malevolent entity. This process facilitates identifying familiar and unfamiliar vulnerabilities inside the cloud environment, encompassing misconfigurations, inadequate authentication mechanisms, insecure Application Programming Interfaces (APIs), data breaches, and more security weaknesses. It contains five stages, as shown in Fig. 4. By identifying vulnerabilities that malicious actors could exploit, penetration testing provides valuable insights and suggestions for improving the security posture and resilience of the cloud environment.

Penetration testing can be conducted at several levels inside the cloud environment, including the network, application, data, and user layers. Penetration testing can be undertaken from several perspectives, including black-box, white-box, or gray-box, depending on the test's scope and objectives. Black-box testing emulates the actions of an external adversary

[17] https://metomic.io/resource-centre/what-are-the-biggest-risks-of-data-leaks

[18] https://cloudsecurityalliance.org/blog/2022/07/30/top-threat-2-to-cloud-computing-insecure-interfaces-and-apis

[19] https://www.darkreading.com/application-security/insecure-apis-a-growing-risk-for-organizations

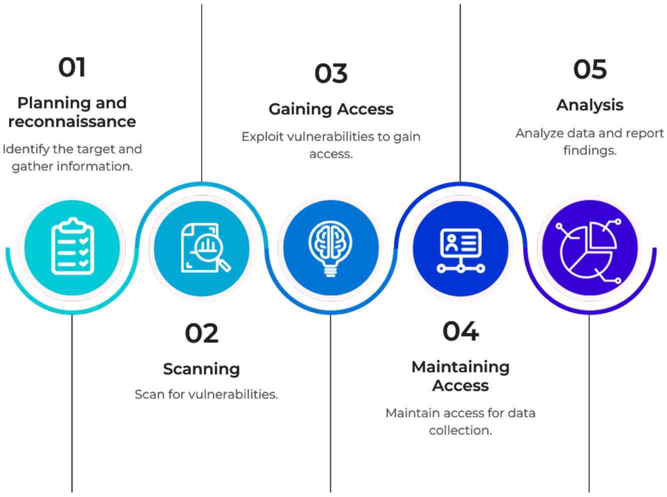
01
Planning and reconnaissance
Identify the target and gather information.
02
Scanning
Scan for vulnerabilities.
03
Gaining Access
Exploit vulnerabilities to gain access.
04
Maintaining Access
Maintain access for data collection.
05
Analysis
Analyze data and report findings.

Fig. 4. Five stages of penetration testing process.

without prior knowledge of the cloud environment. White-box testing involves emulating an internal attacker who possesses comprehensive access to and understanding of the cloud infrastructure. Gray-box testing involves emulating a partially informed adversary with restricted access to or understanding of the cloud infrastructure.

An example of penetration testing within cloud computing is the AWS Penetration Testing service. This service enables customers to seek authorization to conduct permitted tests on their AWS resources. An additional illustration may be in the form of IBM X-Force Red Vulnerability Management Services. This service provides a comprehensive methodology for cloud penetration testing, encompassing many aspects such as infrastructure, apps, data, and users. In our research, penetration testing is critical for assessing cloud security vulnerabilities. This methodology is informed by the insights provided by Vasenius (2022) in his thesis “Best Practices in Cloud-Based Penetration Testing.” Vasenius’ comprehensive analysis of cloud-specific penetration testing approaches, tools, and best practices offers a valuable framework for our penetration testing strategy, particularly in the context of cloud environments and their unique security challenges[20].

In 2022, Khuong et al. in [20] studied a novel architectural approach called deep cascaded reinforcement learning agents (CRLA). This approach was developed to tackle the challenge of large discrete action spaces in an autonomous penetration testing simulator. In such simulators, the number of available actions grows exponentially as the complexity of the cybersecurity network being tested increases. Using an algebraic action decomposition strategy, the Comparative Reinforcement Learning Algorithm (CRLA) demonstrates superior efficiency and stability in determining the optimal attack policy in scenarios characterized by extensive action spaces. This outperforms the conventional deep Q-learning agent, frequently employed as an artificial intelligence approach for autonomous penetration testing.

In 2023, a research paper by Hu et al. in [21] introduced a precise grey box penetration testing methodology known as TAC. This strategy aims to identify instances of identity and access management (IAM) vulnerabilities and privilege escalation (PEs) in third-party services. Third-party cloud security services are frequently employed to identify potential PEs resulting from misconfigurations in IAM. In order to address the dual issues of labor-intensive anonymizations and potential exposures of sensitive information, TAC engages with consumers through a selective querying approach that focuses solely on the relevant information required. The primary finding of this article is that the IAM configuration contains a limited amount of pertinent information for the detection of IAM PE. This study introduces the concept of IAM modeling, which allows for detecting a wide range of IAM PEs by utilizing the limited information obtained from queries. In order to enhance the effectiveness and versatility of TAC, our objective is to reduce customer contacts by implementing Reinforcement Learning (RL) in conjunction with Graph Neural Networks (GNNs). This integration enables TAC to acquire the ability to minimize the number of queries made.

Our approach to penetration testing, especially in the context of mobile cloud computing, is informed by the findings and methodologies discussed by Bakar et al. in [22] provided a comprehensive overview of penetration testing techniques and best practices tailored for mobile cloud environments, which is particularly relevant for our research as it addresses the unique challenges and considerations in these settings. Our penetration testing methodology is significantly influenced by the groundbreaking work of Vuggumudi et al. in [23] outlined an innovative approach known as Compliance Based Penetration Testing (CBPT), specifically tailored for PaaS environments. This approach underscores the importance of a collective approach to security in cloud services, highlighting the necessity for ongoing monitoring and compliance-aligned testing. Such an approach is vital for our research, considering the ever-changing landscape of cloud environments and the continuous evolution of regulatory requirements.

2) Vulnerability scanning: Vulnerability scanning is a technique of systematically discovering, assessing, and reporting security vulnerabilities in a cloud environment and It goes through five stages as shown in Fig. 4. It helps enterprises uncover gaps in their cloud services, infrastructure, and applications that potentially threaten the confidentiality, integrity, or availability of their data and resources. Vulnerability scanning also helps firms comply with security standards and regulations, such as PCI DSS, HIPAA, GDPR, and more. Vulnerability scanning can be performed using numerous tools and approaches, such as automatic scanners, human audits, code reviews, or ethical hacking. Vulnerability scanning can be split into two types: active and passive. Active scanning involves sending probes or queries to the cloud environment to find vulnerabilities and measure their impact. Passive scanning involves monitoring the network traffic or records of the cloud environment to find vulnerabilities and irregularities.

An example of vulnerability scanning in cloud computing is AWS Amazon Inspector, which is an automated security evaluation tool that helps clients enhance the security and compliance of their AWS applications[21]. Another example is

[20] https://www.utupub.fi/handle/10024/173476

[21] https://docs.aws.amazon.com/inspector/latest/user/what-is-inspector.html

Digital Defense Frontline VM, which is a cloud-based vulnerability management tool that delivers continuous scanning and reporting of cloud assets. Our research methodology for vulnerability scanning incorporates insights and techniques from Mitchell and Zunnurhain's (2019) study, "Vulnerability Scanning with Google Cloud Platform," presented at the CSCI conference [24]. This paper presents a detailed examination of vulnerability scanning methods within the Google Cloud Platform, offering a specific lens on how these scans can be effectively utilized in cloud-based environments. Their work provides a valuable perspective on the practical applications and challenges of conducting vulnerability scans in such settings, directly relevant to our research focus.

We have heavily referenced the comprehensive analysis by Kritikos et al. [25] that meticulously evaluated the latest tools and databases pertinent to vulnerability assessment in the cloud. The survey's detailed insights into these tools' performance, range, and functionalities significantly influence our methodology, particularly in selecting and implementing the most effective techniques for extensive vulnerability scanning in cloud-based applications.

C. Future Trends in Cloud Computing Security

As cloud computing evolves, staying ahead of emerging security challenges is crucial. Cloud security landscape is expected to undergo significant changes in the coming years, influenced by technological advancements and shifts in cyber threats. Below are key trends that are likely to shape the future of cloud computing security:

1) Increased reliance on AI and Machine Learning (ML): AI and ML are set to play a pivotal role in cloud security. These technologies can analyze vast amounts of data to identify patterns indicative of cyber threats, enabling proactive threat detection and response. As cyberattacks become more sophisticated, AI-driven security systems will be critical in identifying and neutralizing threats before they can cause damage[26].

2) Greater emphasis on zero trust architectures: The traditional security model of 'trust but verify' is shifting towards a 'never trust, always verify' approach. Zero Trust Architecture (ZTA) will become more prevalent, where security protocols require verification from everyone attempting to access resources in the network, regardless of whether they are inside or outside the network perimeter. This approach minimizes the risk of internal threats and data breaches [27].

3) Expansion of edge computing: As the Internet of Things (IoT) expands, edge computing will become more common, processing data closer to where it is generated rather than in a centralized cloud-based data center. This shift will require new security strategies to protect data across more dispersed networks[22].

4) Enhanced regulatory compliance: With the growing concern over data privacy and security, regulatory compliance will become more stringent. Companies must adapt to these regulations, which will likely require more robust security measures to protect sensitive data, especially in industries like healthcare and finance [28].

5) Blockchain for improved security: Blockchain technology is expected to be increasingly adopted for cloud security because it offers decentralized security and reduces single points of failure. Its potential for ensuring data integrity and preventing tampering will make it a valuable tool in enhancing cloud data security[23].

6) Rise in cybersecurity mesh: Cybersecurity mesh is a flexible, modular approach that integrates various security services. This trend will allow organizations to deploy and integrate security where it's most needed and manage it in a more unified way, thus improving the overall security posture[24].

V. Conclusion

Cloud computing has rapidly changed how firms manage their data and IT demands, providing flexibility, accessibility, and cooperation. This change has also revealed many security risks that must be addressed to secure sensitive data and cloud settings. Mismanaging cloud resources or data frequently results in cloud misconfiguration and data leakage. These vulnerabilities can cause data breaches, compliance violations, and financial losses for cloud providers and clients. Additionally, cloud-based shared technological vulnerabilities are risky. Cloud computing allows numerous enterprises to share infrastructure and platforms, which can expose sensitive data to breaches, service outages, and resource misuse if not properly secured. Quick patching, resource isolation, and monitoring can mitigate these shared vulnerabilities. Furthermore, understanding the shared responsibility concept is crucial. This model defines cloud service providers and customer security duties. Organizations must know how to secure their cloud resources and data and use cloud providers' tools and services to improve security. Cloud services and emerging technologies like IoT and AI drive exponential data growth in cloud environments, creating unique problems. Securing varied cloud environments becomes more difficult as firms adopt multi-cloud strategies. Cloud data security and compliance need risk assessments, careful cloud service provider selection, and industry-specific requirements. Ransomware, zero-day exploits, social engineering, and supply chain assaults are becoming more sophisticated, requiring cybersecurity specialists, corporations, and researchers to share knowledge and information. To succeed in this changing world, enterprises must take a proactive, holistic approach to cloud security, covering technological and organizational factors. In an ever-changing digital world, organizations may protect their data, manage risks, and maintain their reputation and financial stability by remaining educated about new threats and vulnerabilities, applying best practices, and enhancing their cloud security maturity.

Acknowledgment

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[22] https://techresearchonline.com/blog/edge-computing-an-extension-of-cloud-computing/

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DDoS Attacks Detection in IoV using ML-based Models with an Enhanced Feature Selection Technique

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***Abstract*—The Internet of Vesicles (IoV) is an open and integrated network system with high reliability and security control capabilities. The system consists of vehicles, users, infrastructure, and related networks. Despite the many advantages of IoV, it is also vulnerable to various types of attacks due to the continuous and increasing growth of cyber security attacks. One of the most significant attacks is a Distributed Denial of Service (DDoS) attack, where an intruder or a group of attackers attempts to deny legitimate users access to the service. This attack is performed by many systems, and the attacker uses high-performance processing units. The most common DDoS attacks are User Datagram Protocol (UDP) Lag and, SYN Flood. There are many solutions to deal with these attacks, but DDoS attacks require high-quality solutions. In this research, we explore how these attacks can be addressed through Machine Learning (ML) models. We proposed a method for identifying DDoS attacks using ML models, which we integrate with the CICDDoS2019 dataset that contains instances of such attacks. This approach also provides a good estimate of the model's performance based on feature extraction strategic, while still being computationally efficient algorithms to divide the dataset into training and testing sets. The best ML models tested in the UDP Lag attack, Decision Tree (DT) and Random Forest (RF) had the best results with a precision, recall, and F1 score of 99.9%. In the SYN Flood attack, the best-tested ML models, including K-Nearest Neighbor (KNN), DT, and RF, demonstrated superior results with 99.9% precision, recall, and F1-score.**

Keywords*—*Random forest; IoV; DDoS; feature selection

I. Introduction

After the significant development in the number of vehicles, where it was found that there are one billion vehicles around the world, with an expected doubling by 2035, and the accompanying increase in congestion and traffic accidents, driving has become difficult and dangerous. The idea of the IoV has been formulated to address these challenges. IoV is at the heart of the new generation of intelligent transport systems, representing a new trend of future development. The IoVs is defined as a distributed network with an open, integrated, and credible system that provides a safe and smart environment. This system consists of vehicles, individuals, infrastructure, and networks related to smart systems. It depends on the sensors integrated into modern vehicles, which are linked to the intelligent transport network. Initially, the VENAT network was allocated with its limited ability to use the information provided by mobile devices. Currently, in the 5G era, the IoV has evolved, and its ability to deal with data during communication between vehicles and the network, vehicles with each other, or vehicles with people has significantly improved. In our opinion, safeguarding the communication between vehicles and achieving a more effective network requires the use of ML techniques to provide the necessary protection for wireless communications and efficient detection of attacks, as well as the detection of misconduct and the concept of trust. It provides electronic security services for road services, vehicles, and the information required to enhance security operations and take proactive steps against threats [1]. IoV networks are characterized by many features such as scalability, dynamic topology changes, variable network density depending on city conditions, geographical location energy, security, and privacy. The IoVs involves massive dynamic data, making security and privacy major concerns. One of the most significant challenges in reducing penetration is security and privacy. Types of security attacks include authentication attacks such as jamming, eavesdropping, and Sybil attack. As a consequence, constructing a protection system based on ML techniques, algorithms, and strong authentication is required to maintain anonymity traceability, and wireless communication protection attributes to connect securely and effectively [2]. The main contribution of this research are:

1) Developing a ML based system to prevent communication errors that could cause traffic disruptions or accidents between networks and interconnected vehicles.
2) Developping IoV protection technologies and increased security investment.
3) Ensuring the security for vehicle exchange data storage and infrastructure.

The rest of the paper is organized as follows: Section II presents related work. In Section III, describes Proposed models. Section IV presents our implementation and experiments. Section V presents an experimental evaluation of the performance our heuristic. Section VI concludes the paper and discusses some future work.

II. Related Works

A. Internet of Vehicles (IoVs)

The IoV appeared as a new attempt with the emergence of Ion technologies in the field of wireless cooperation with the

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emergence of the Internet of Things (IoT). It is a common complex network in which real communication takes place in the IoV between two or more entities in which many different technologies are used such as the navigation system, mobile, sensors, and the instruction system. IoV has gone through stages with a history of innovation and development through modifications in size, style, and decoration, while technological improvement has pushed mobile phones for cars to the latest trends. Analytical approaches have improved IoV's understanding of traffic and telemetry trends. Advances in information systems, detection and communication capabilities, and intelligent physical infrastructure create new opportunities to reduce real congestion and response challenges. Real-world data flows ingest a heterogeneous amount of data and drive data processing and secure transmission between entities based on this data. Vehicles are controlled and directed in realtime [1]. Analytical approaches have improved IoV's understanding of traffic and telemetry trends. Advances in information systems, detection and communication capabilities, and intelligent physical infrastructure create new opportunities to reduce real congestion and response challenges. Real-world data flows ingest a heterogeneous amount of data and drive data processing and secure transmission between entities based on this data. Vehicles are controlled and directed in real- time [1].

B. IoV Architecture

The IoV architecture is composed of four main layers: environment detection, network, computation, and application layer. The environmental detection layer is tasked with collecting data from the environment around the vehicle, such as object locations, road conditions, and driving habits, via an RFID card and sensors embedded inside vehicles. The network layer is responsible for providing all required types of connectivity, such as short-term communication (for example, Zigbee, Bluetooth, Wi-Fi) or cellular network (for example, WiMAX or 4G/LTE), between the objects of the vehicle's environment and its connection to the cloud. The computing layer is accountable for processing, storing, and resolving the collected data necessary to provide safety, comfort, risk situations, and efficiency. The application layer offers both open and closed services. Open services refer to online applications provided by Internet service providers and third-party service providers (for example, real-time traffic services and online video delivery). In contrast, closed services refer to a particular IoV application (for example, a control panel and traffic instructions) [3].

C. Characteristics of IoV

- High Scalability: A city can contain millions of vehicles and sensors that require an extensive network. This network must be scalable to accommodate the continuous increase of vehicles.
- Dynamic structure: Many components of an IoV interact with each other (particularly vehicles) moving at high speed, rapidly changing the network topology.
- Geocommunication: The vehicle network uses geocommunication, but in IoV nodes are not predetermined when packets are sent and their speed varies based on the geographical area of the sites [4].

D. Attack Types in IoV

IoV security is a highly developed field that requires serious attention. Any simple mistake or security failure can cause a catastrophe in terms of human and economic losses, causing damage to vehicles and road infrastructure.

1) Authentication attacks Sybil Attack: The Cyber node detects the imposition of an attack as it damages the systems in the wireless network and thus increases the likelihood of leakage of vehicle data [5], [6]. GPS deceives: This type of attack by giving deceptive information regarding vehicle speed and geographic location data of other vehicles as undeniable evidence and thus helps to avoid tracing causing unpredictable damage to property and providing false evidence [7].
2) Disguise attacks. In the network environment, each entity has its identity, in disguise attacks a similar identity is given to several nodes simultaneously causing chaos in IoV systems [2].
3) Availability attacks. Availability attacks are the main objective. These attacks is to decrease transmission power and bandwidth and thus collapse the IoV system by controlling or destroying it completely to make a significant impact on the IoV system [2].
4) Eavesdropping attacks. Resource and data are the main components of the vehicle internet system and therefore care must be taken of sensitive data and that unreliable nodes connect to it. In this type of attack, the data is stolen by intercepting and eavesdropping on it [4].
5) Jamming attacks. These are interference attacks. This type of attack aims to camouflage, replay, illusion, and tamper with data to cause chaos and confuse the movement of the regime [4].

III. DDoS Attacks Detection

Several studies and solutions have been provided by researchers in the same study area in this part, and the goal of the article, as well as the research summary, such follows: In the IoV network system setting, high performance is challenging to deliver. This suggests using the Double Deep Q-learning Network (DDQN) model. Overestimation as a Vehicle Internet is prevented. In actual complicated settings, it can deliver higher-quality network services and guarantee improved computing and processing speed. The IoVs are intelligent transport, internet is a new application of the Internet. This research offered several innovative and practical solutions in this area. The algorithm relies in its work on calculating the discharge based on the DDQN network model and then the network tasks are allocated using asynchronous processing technology [8]. The use of wireless communications between vehicle nodes and DR infrastructure makes them vulnerable to various types of attacks. In this regard, ML and its variants are gaining popularity for detecting attacks and dealing with various kinds of security issues in vehicle communications. The research also explains the basics of vehicle networks and the types of communication related to them and how to find solutions using machine learning algorithms [6]. This research focuses on applying machine learning to gather data on vehicles along a GPS route and using the Gaussian process to anticipate traffic based on three groups: training and forecasting groups, bandits, and other variables. Additionally, traffic is forecast for the present and the future, and shortly, the average speed of cars during these times is evaluated [9], [3]. The development of autonomous intelligent cars can help solve transportation problems. The IoT has developed into an advanced and intelligent system called the IoVs, but it is still vulnerable to assaults from this study. To identify dangers. K fold the study discovered that the KNN-CART algorithm delivers the greatest accuracy, with respective values of 99.79% and 99.79% [10]. The Social IoT (SIoT) is the level of enabling awareness where it permits things to interact with one another. Social IoV (SIoV) will transform the automotive industry. The scalability of relying on online technologies is the main topic of this research. It is important to concentrate on the class structure and the function of each system entity while taking into consideration the dynamic nature of the study of SIoV's structure and emphasizing the unique use cases [11].

A. *Machine Learning-based Models*

Since ML was first used as a self-learning method for checkers in 1959, it has been widely used in all areas of the network to improve work performance. The typical model of machine learning consists of three stages:

- The training stage, where the advantages are extracted from the initial data.
- The testing stage, where a new set of data is tested based on the educational experience gained in the training phase by the ML model.
- The prediction stage, where the efficiency of the ML model's work is evaluated based on quality measures.
- ML shows outstanding results in the field of detecting anomalies due to its ability to learn patterns and behavior. Thus, it is the best solution to distinguish deviant from normal behavior, classify attacks, and discover their types.

ML based DoS/DDoS security modeling is shown in Fig. 1:

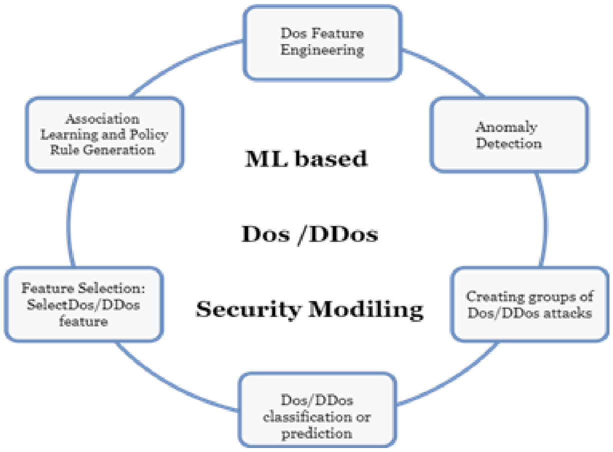

Dos Feature Engineering
Anomaly Detection
Creating groups of Dos/DDos attacks
Dos/DDos classification or prediction
Feature Selection: SelectDos/DDos feature
Association Learning and Policy Rule Generation
ML based
Dos /DDos
Security Modiling

Fig. 1. ML DoS/DDoS Security modeling process.

B. *Machine Learning Models for IoV Security*

- Supervised Learning: It is necessary to assign a value for the input and name a corresponding name for each input of the dataset through the relationship between the input models and the naming of the training group. The algorithm assigns newly acquired samples of test data and applies them to secure vehicle networks. Supervised training is classified as classification and regression, which is one category of popular classification models used in vehicle systems: KNN, DT, Naive Bayes (NB), SVM, RF, and LR models. Logistic regression and random forest models are applied in vehicle networks in applications such as driver fingerprints and types of misconduct.
- Unsupervised Learning: It consists of input values only in their training set and no labels for the dataset. Finding hidden patterns of data focuses on unclassified information. The algorithms used are more efficient and faster in data processing in aggregation applications. The most common assembly mechanisms in vehicle networks include k-means clustering, Hidden Markov Model (HMM), and NN [12].

IV. Proposed Models

In IoV, vehicles can connect and communicate through Vehicle-to-Road (V2R) communication, Vehicle-to-Infrastructure (V2I) communication, as well as communication with sensors Vehicle-to-Sensor (V2S), and Vehicle-to-Vehicle (V2V) communication. All of these communications take place through the wireless network. Of course, all of these communications must have a high level of protection to preserve privacy while continuing to improve it. Current network security technologies and products, such as network firewalls, intrusion detection systems, intrusion prevention systems, web firewalls, and other security devices, are used to enhance security. The user shares much information such as location, as well as many behavioral patterns and some involuntary information such as pedestrian images and private property. This information may be subject to violation, which raises concerns, and this problem cannot be solved by reducing the sharing of information but rather by finding solutions that make it trustworthy. This part will go through the methodology that depends on detecting attacks and penetrations to take urgent measures to protect the IoVs and maintain the privacy of information by monitoring the packets that pass through the IoV network and taking proactive measures to prevent these attacks to maintain a safe communication environment and achieve security requirements [12]. Our proposed model is shown as in Fig. 2.

A. *Details of the Research Methodology*

In this part, we learn how the effectiveness of the security model, as the study was based on the efficiency of the proposed model in detecting security attacks. The CICDDoS2019 dataset with ML machine learning models to detect the ability to detect a DDoS attack [13]. We analyzed the results of DDoS attacks through the machine learning model, which goes through three stages: the training stage, where features are extracted from the raw data, then the testing stage by ML models, where

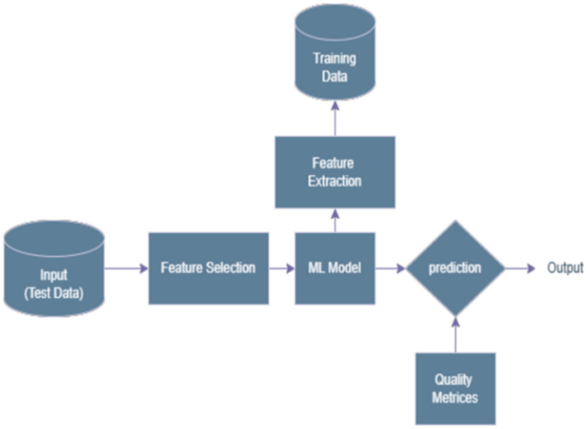


Fig. 2. The proposed method flowchart.

the dataset acquired during the training stage is tested, and the last stage is prediction, where the efficiency of the ML model is evaluated. Algorithm 1 shows the characteristics of the dataset used [14], [15]. Data preprocessing before building the ML model plays an important role in the accuracy of the machine learning models. The features were reduced from 80 to 47 using chi2, which further reduced the test time while Benign and DDoS attacks (UDPSYN) were replaced by [0.1] respectively. From a balancing act, a K-fold where k=5 was used to evaluate and compare ML models [16].

B. Intrusion Detection System (IDS)

IDS intrusion detection systems must be continuously updated to prevent attacks that develop daily. Some algorithms work well with some attacks and perform poorly with others. An ML-based IDS system can extract complex behavioral attributes that can be improved and also include dataset preprocessing [17] as in Fig. 3.

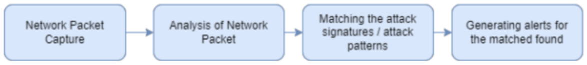

Network Packet Capture
Analysis of Network Packet
Matching the attack signatures / attack patterns
Generating alerts for the matched found

Fig. 3. Architecture of IDS.

There are two problems related to IDS:

- The high rate of false alarms, which are triggered by warnings for unlimited violations and many violations that have not yet been identified.
- New attacks are not easily detected, thus increasing the interest in using ML.

C. CICDDoS 2019 Dataset

This dataset contains the latest and most realistic DDoS attacks. It was developed at the Canadian Institute of Cybersecurity to cover normal traffic. DDoS attacks are the most common and resemble real traffic, network, and properties. It consists of a set of servers and software such as computers, switches, and traffic generators. The dataset provides a knowledge file of the attacks that were performed and models about the applications, networks, and protocols. The dataset has been studied so that it can simulate the types of attacks, consisting of 47 traffic characteristics from the original information traffic consisting of UDPSYN. The prediction and evaluation tests and performance measures are used as evidence for the results and comparisons to analyze the models [17]. To detect DDoS, a group of data was proposed, but none of them were able to detect it. The CICDDoS2019 dataset deals with these problems to achieve optimal performance. This group consists of benign and malicious DDoS attacks. The dataset specifications are listed, and the dataset files use binary classification. The dataset includes missing and duplicate data records processed by applying feature engineering or by disposing of missing records. Feature selection is done using chi-square features. It calculates chi scores to rank features. Feature selection techniques can obtain the optimal feature for target DDoS variables using machine learning algorithms [18].

D. Machine Learning Models

After obtaining the optimal feature sets, KNN, DT, NB, SVM, RF, and LR models are used as models for intrusion detection and attack classification. Using the set and features obtained, the performance of ML techniques is compared in terms of accuracy, Recall, F1, and Precision. The main objective of the research was to resolve the effect of feature selection techniques on detection accuracy, Recall, F1, and Precision. Here is a quick rundown of these methods:

1) Logistic Regression (LR): This adapted linear regression approach is commonly employed in addressing classification challenges, as it has the capability to predict the assignment of an observation to a particular class. Its practical applications include tasks like spam filtering and intrusion detection. In instances where the anticipated likelihood surpasses a predefined threshold, it is anticipated that the occurrence aligns with an attack, given its position above the threshold. Conversely, if the anticipated likelihood falls below the threshold, the occurrence is categorized as normal. This is determined by the following equation:

$$h_{(\theta(x))} = \sigma(\theta^T X) \tag{1}$$

where, $\theta(x)$ is the hypothesis, x is the input feature vector, θ is the LR parameters, and σ (r is a sigmoid function that is used for the threshold definition. The sigmoid is defined as:

where, r is the term $(\theta T x)$ in the previous equation, the output is between (0:1) [19].

$$\sigma(r) = \frac{1}{1 + e^{-r}} \tag{2}$$

2) Naive Bayes (NB): A simple but effective probabilistic algorithm with real-world applications ranging from product recommendations to controlling self-driving vehicles. Using Bayes' theorem for classification, NB is superior to other alternative techniques. NB assumes normally distributed data and defines the conditional probability of the class. Bayes' theorem provides a systematic method for calculating probability based on the advantage of independence assumptions.

$$P(L|X) = \frac{P(X|L)P(L)}{P(X)} \tag{3}$$

where, $P(L|X)$ the posterior probability of class L is, P(L) is the prior probability, $P(X|L)$ is the likelihood function, and P(X) is the probability. The training set is used to estimate these parameters [20].

3) k-Nearest Neighbor (KNN): A method used to classify objects. Based on the learning data closest to the object, the comparison is based on previous and current data. It is a basic strategy that uses new instances from a test set to the closest instance in the training set. The number of neighbors and the distance are the two basic parameters of the KNN technique. The algorithm calculates the distance to the nearest neighbor by applying the Euclidean distance formula and is known as:

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{4}$$

where, $d(x, y)$ is a Euclidean distance function between the two samples, x_i is the initial observation, y_i is the second sampling of the information, and n represents the observations [21].

4) Decision Tree (DT): DT classifiers are one of the most popular ways to represent classifiers for data classification. It is one of the widely used techniques in data mining and can handle a vast amount of information. It is likened to a tree with its branches and leaves, where the inner node refers to the rules of classification, the leaves refer to the chapter label, and the branch refers to the results. The greatest degree of information acquisition is used as a measure for choosing the optimal traits and is used to construct the decision node, by creating a new sub-tree under the decision tree. The cycle continues until all the results of the subsets have the same value, at which point the process stops, and the final value is calculated as an output value. Gini inclusions were used as division criteria, as shown:

$$G(D) = \sum_{i=1}^{C}(P(i) * (1 - P(i)) \tag{5}$$

where, D is the training dataset, C is a collection of class labels, and $p(i)$ is the proportion of samples having the class label i in C. When there is just one class in C, the Gini impurity is zero [22], [23].

5) Random Forest (RF): ML technology is a supervised technique and gives excellent results. It consists of several trees planted randomly, and each leaf node is named for each tree. Each internal node contains a test that divides the data space to be classified by sending images to the bottom of the tree and collecting the leaf distributions obtained. The best way to determine the number of trees necessary is to compare forest predictions with subset predictions from the forest to produce a model that predicts the dataset more accurately and consistently. Its advantage lies in the fact that it is highly adaptable and enables it to solve classification and regression issues [23]. The general equation for a random forest model can be written as:

$$y = f(x) = \sum(i = 1\ to\ n)\ Ti\ (x)/n \tag{6}$$

where, y is the predicted outcome, x is the input feature vector, n is the number of DTs in the forest ,and $Ti(x)$ is the prediction made by the RF.

6) Support Vector Machine (SVM): Supervised learning models with machine learning analyze the data used in classification and regression analysis and can handle linear datasets. The main goal of SVM is when the problem is not linearly separable, then it will be with a nonlinear kernel such as RBF for nonlinear mapping to transform the unique form of training data into a higher dimension through the equation.

$$K(x, y) = e^{\frac{||x-y||^2}{z\sigma^2}} \tag{7}$$

where, σ is the variance and the SVM hyper-parameter, $||x - y||$ is the Euclidean distance between two points [24].

E. Executing DDoS Attacks

A subclass of DoS attacks disrupts normal traffic for a particular target. DoS attacks from multiple sources are performed simultaneously. On the IoVs, malicious vehicles can launch DDoS attacks, so it is important to detect attacks in real-time. Intended to flood threats to undermine the availability of vehicular Internet operations to perform DDoS attacks through an SSH-based master agent. The types of attacks described in the dataset are as follows: UDP-Lag attack is an attack that disrupts the communication file between the server and the client, and a SYNflood attack that controls the transmission to drain the victim's resources and affects them by not responding [25]. ML is one of the most popular methods, as it is considered a powerful model that predicts modern forms of DDoS attacks, as it analyzes them in real-time and classifies them into normal behavior or abnormal behavior. It also predicts attacks before they occur based on DDoS modeling and many algorithms such as KNN and SVM [21]. DDos attack in IoV is drawn in Fig. 4.

F. Confusion Matrix

The confusion matrix as in Fig. 5 is a measure of self-learning rating performance. It is a table of type $n * n$ where n is the number of possible labels for the data. The confusion matrix plays an important role in determining performance. In our model, we have three types of values: Benign , UDPLag, and SYN.

Most of the measures mentioned above can be calculated from the confusion matrix illustrated in Fig. 5, which is a typical tool used to record model performance. The rows in the matrix are the actual class, and the columns are the expected class. In the confusion matrix, TN, FN, FP, and TP represent true positives (the number of negative samples correctly classified, similar definition for the rest), false negatives, false positives, false negatives, and true positives, respectively. This is especially important under imbalanced learning conditions [26].

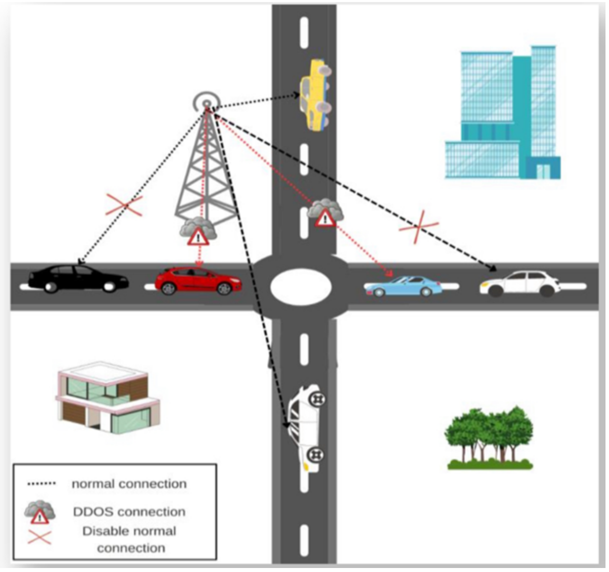
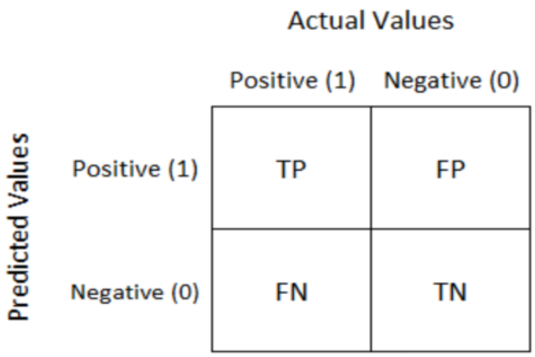


Fig. 4. DDoS Attack in IoV.



		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Fig. 5. Confusion matrix [24].

G. Data Oversampling

Sampling is the most used method to solve the problem of class imbalance. The process of data sampling involves creating a data set by adjusting the number of samples of the majority class in the unbalanced data set and it occupies the largest part while the minority class occupies the smallest part. The sampling method is classified as a reduction or oversampling method, depending on which of the two categories is the number of samples [27].

• Random oversampling Random oversampling is done by increasing the samples of the minority group randomly, which means increasing the cases corresponding to the minority group by repeating them at a certain rate. It is considered an additional advantage as it does not cause the loss of any information. (a) Oversampling increases the number of instances of the training set, and random oversampling increases the training time of the model [28], [29]. Algorithm 1 shows the random sampling for the initialization of the backing sample.

H. MinMax Scaler

MinMax Scaler is one of the most popular scaling algorithms. The main idea of the linear data conversion algorithm where the algorithm assigns the value of V from the variable to the value of V using the formula:

$$X_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{8}$$

The goal is to measure the variable MinMax in the interval [0,1] using linear assignment, meaning that the minimum and maximum value of a feature/variable is going to be 0 and 1, respectively [30].

I. Feature Extraction

The feature plays a big and important role in the performance of the model. Excluding or including features leads to the deterioration or improvement of the model. Accordingly, the features are the only ones relevant to the improvement of the model. The main objective of the classification is to know the benign and malicious traffic. The model is trained using the selected features before the training ends. The K1Fold is validated to divide the model into training and testing and also serves to help evaluate the model. The model is divided into five groups of equal size, four groups are trained, and one group is tested. The process is repeated ten times. The performance measures used in the model are feature selection. Reducing the number of features contributes to reducing the processing time that machine learning algorithms take. We can calculate the Chi-square between each element and the target, then select the ideal number of features with the best Chi square scores [31], [32].

$$FE = REM + RMD + DER \tag{9}$$

Were,

- FE Feature Extraction as shown in Algorithm 3,
- REM: Review Existing model,
- RMD: Remove missing data, and
- DER: Domain expert review

The argmax function returns the index of the element in the list that has the maximum value. You can use any appropriate performance metric to evaluate the models, such as accuracy, precision, recall, F1-score.

V. Experiments

In this section, we will learn how to measure the effectiveness of the security model, as the study was based on the efficiency of the proposed model in detecting security attacks. We analyzed the results of the attacks through a typical ML machine learning model where the features are extracted from the raw data and tested by the ML model. The CICDDoS2019 dataset is then tested and predicted, and the working efficiency of the ML model is evaluated.

Algorithm 1 Feature Extraction to optimize features
Input: A large Number of Features
Output: Optimized Features

```
1) Start
2) Extract Datasets
3) Delete missing data, Feature selection using domain expert
4) Data pre-processing
5) Use 10-fold cross-validation.
6) While all data sets are trained and test
  a. Split data into k-5 and 10-fold cross-validation.
  b. Model fitting
  c. Model Evaluation
7) End while
8) End
```

A. Models Implementation

ML models and configurations are evaluated based on evaluation scales: TP represents the true positives; TN represents the true negatives through the criteria.

1) Data preprocessing: Processing the dataset is the main stage before entering the data into the ML to achieve high performance. There are many challenges in the dataset such as missing values, categorical features, and class imbalance. Also, useless features may affect the performance of the selected ML.

2) Feature selection: Feature selection is necessary to detect intrusions, get the best score for the prospective feature, and choose the best. Where the different features should be checked gives a positive and negative category for each of them and thus get rid of the useless ones to improve the performance. The feature is selected using Chi2 technology, as it achieves better performance for many classification problems. A selection strategy is used to exclude the features using the null hypothesis. A higher Chi2 value means that the feature is more significant [33].

$$x^2 = \sum_{i=1}^{m} \sum_{j=1}^{n} (\frac{O_i - E_i}{E_i})^2 \tag{10}$$

Where: m represents the number of features, and n represents the number of classes and O_i is any observed frequency and E_i expected frequency [34].

3) Data normalization: The numerical values in the dataset pose a challenge to the classifier during training. Maximum values must be set for each property within the range of (0, 1). Values outside the range can lead to incorrect results, as the technique may skew to the higher advantage. Data normalization plays a vital role in outperforming features with higher values over features with lower values. The data is oversampled to balance the class distribution, as presented in Eq [35], [36]

$$Z = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{11}$$

where x is the feature value, Z is the value after normalization, and x_max and x_min are the maximum and minimum values of the feature.

4) Data cleaning: The CICDDoS2019 dataset contains missing values and infinite values. The values are processed in two ways: In the second dataset, the infinite values are replaced by extreme values, and the missing values are replaced by averages. Only attack information packets were used to evaluate the proposed approach. Data packets representing normal network traffic are discarded in both groups, which improves accuracy and reduces computing time.

B. Proposed Models

In the dataset, the selected methods were used for training and tested by different parameters in feature engineering for intrusion detection. We selected different workbooks using: Accuracy, Recall, Precision, and F1 point. The methods used have shown strong performance in creating IDS. We explore the following strategies: K- Nearest Neighbor (KNN), DT, NB, SVM, RF, and LR.

C. Experiments

The CICDDoS2019 dataset and ML machine learning models were used to detect DDoS attacks. The implementation was done using Python 3.10 with many libraries such as Pandas, NumPy, Seaborn, and Matplotlib.pyplot.

VI. Results and Discussions

In this section, we review all the features for analyzing system performance, detecting events that are not compatible with normal behavior, confirming auditing and examining this data, and quality measures for the fully utilized ML model to be able to take a proactive step to avoid potential damage to vehicular Internet networks. Outstanding results appear in the field of discovering anomalies in time series data due to its ability to learn patterns and complex behavior. Therefore, it is the appropriate solution to distinguish deviant behavior from normal behavior.

A. Results Measurement Formulas

- Accuracy: It is responsible for evaluating classification models by depicting the proportion of correct predictions in the dataset, and is based on:
$$Accuricy = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$
- Recall: measures the ratio of correctly identified labels to the total number of instances and is based on the following:
$$Recall = \frac{TP}{TP + FN} \tag{13}$$
- Precision: measures the ratio of correctly selected labels to the total number of positive ratings:
$$Precision = \frac{TP}{TP + FP} \tag{14}$$
- F1: points measure the harmonic mean of precision and recall [37].

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{15}$$

B. Results Analysis

Exploit-based attacks are attacks in which the attacker's identity is kept hidden by a third party. Packets are sent by the attacker to mirroring servers with the source IP address changed to the target victim's IP to confuse it. These attacks are carried out through transport layer protocols such as TCP and UDP. These include exploits based on SYN floods and flooding attacks such as UDP floods. The dataset includes CICDDoS2019 token 25 which consists of UDP, and SYN traffic. It is used to analyze system performance and discover events that are not consistent with the normal behavior of the network. Through mathematical models of ML algorithms: LR, KNN, DT, NB, RF, and SVM. we trained the models and performed validation to calculate the evaluation metrics.

C. Description of Network Attacks

- UDP Lag: UDP Lag attack is an attack that disrupts file communication between a client and a server. The attack can be carried out in two ways: through hardware switching, known as delay switching, or through software running on the network and consuming the bandwidth of others. It involves a special UDP stream that consumes more bandwidth while decreasing the number of packets.
- SYN Flood: In addition, SYN Flood is a type of TCP flood that targets the initial handshake of the TCP connection. The SYN flood sends a large volume of packets to the target server.

D. Dataset Scenarios

The files contain all the packets, and the CSV files provide a simpler way to load the data. These files consist of features extracted from the original pcap and are fixed- size files. The files are converted from pcap to CSV by capturing all sides of the network traffic data. Along with the innocuous packets, the traffic is then broken down into smaller data through parallel conversion using TCP Dump. The features are then extracted using chi2 and stored in separate CSV files. The extracted features are used to aggregate the captured values to reduce discrepancies in data size.

E. Results Discussion

In this section, we present the evaluation of the performance of classification algorithms, namely LR, KNN, DT, NNB, RF, and SVM models.

We trained the models and performed validation to calculate the evaluation metrics. The evaluation scheme is a performance evaluation, as it determines the efficiency and robustness of the proposed scheme. A dataset with identical characteristics is needed for real traffic and DDoS traffic flows, so we evaluated the performance of classification algorithms using the CICDDoS2019 dataset. The performance of the six-model considering UDP-Lag attack is shown in Fig. 6.

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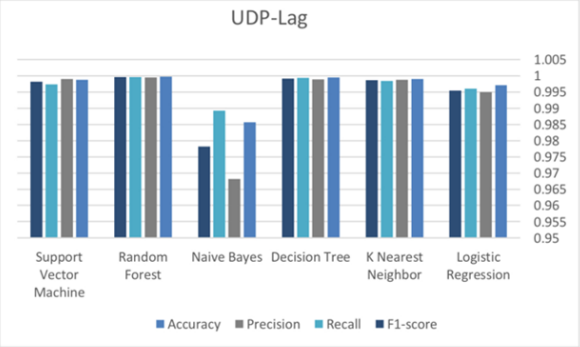

Fig. 6. Performance for proposed ML models for UDP-Lag attack.

We adopted six ML models for binary classification (benign or malicious). The results showed high accuracy in Random Forest, k Nearest Neighbor algorithm, and Decision Tree. These results demonstrate how ML models can be used to classify attacks against IoV. These models may face challenges in classifying other attacks as benign or malicious, and despite the similarity in patterns, the classification is successful. The accurate results are shown in Table I.

TABLE I. Proposed ML Models Results for UDP-Lag Attack

Model + chi2 FE	Accuracy	Precision	Recall	F1score
LR	0.9950	0.992	0.9856	0.9875
LR+chi2	0.9954	0.996	0.9949	0.9971
KNN	0.9976	0.9974	0.9967	0.989
KNN+chi2	0.9986	0.9984	0.9987	0.999
DT	0.9971	0.9954	0.9949	0.9925
DT+chi2	0.9991	0.9994	0.9989	0.9995
NB	0.9722	0.9792	0.9661	0.9817
NB+chi2	0.9782	0.9892	0.9681	0.9857
KNN	0.9980	0.9924	0.9957	0.991
KNN+chi2	0.9986	0.9984	0.9987	0.999
RF	0.9976	0.9962	0.9943	0.9972
RF+chi2	0.9996	0.9996	0.9995	0.9997
SVM	0.9962	0.9943	0.991	0.9916
SVM+chi2	0.9982	0.9973	0.999	0.9988

The best ML models tested in the UDP Lag attack outperformed. The DT model, and RF model had the best results with a precision, recall, and F1 score of 99.9%. For the SYN flood, the performance of the six models is presented in Fig. 7.

In the SYN flood attack, the best tested ML models appeared superior, with KNN, DT, and RF models having the best results with 99.9% precision, recall, and F1-score. The details results are shown in Table II.

The confusion matrix plays an important role in determining performance. The Confusion matrix for UDP-Lag and SYN Flood are shown in Fig. 8 and 9 .

VII. Conclusions and Future Work

We presented a new and large-scale IoV data set for the training and evaluation of threat detection systems. The results reveal high response rates for the models with the selected features. A system based on ML models has been developed

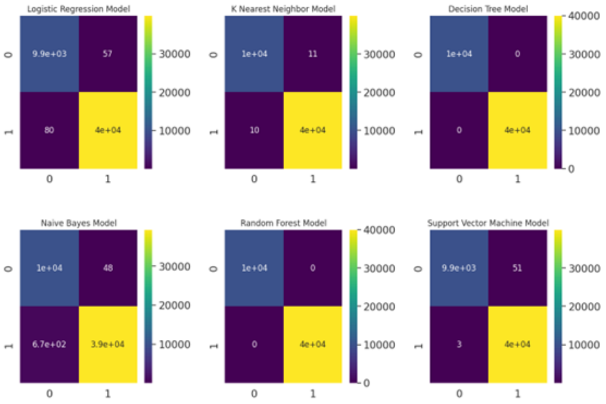

Fig. 8. Confusion matrix for UDP lag attack.

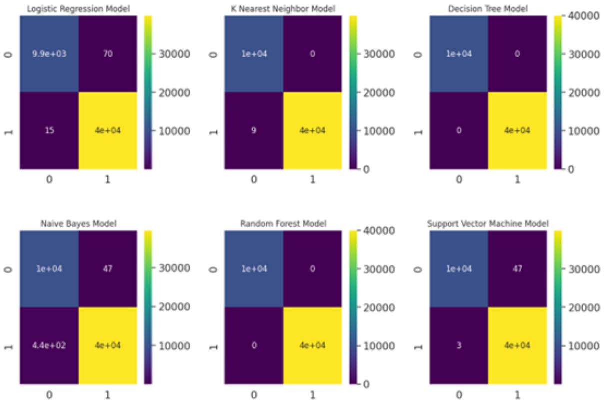

Fig. 9. Confusion matrix for SYN flood attack.

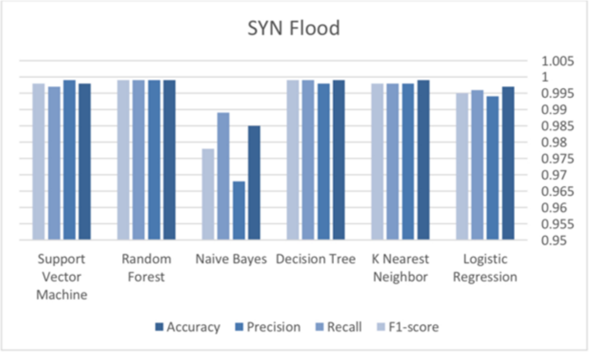

Fig. 7. Performance for proposed ML models for SYN flood attack.

TABLE II. PROPOSED ML MODELS RESULTS FOR SYN FLOOD ATTACK

Model + chi2 FE	Accuracy	Precision	Recall	F1score
LR	0.9970	0.9972	0.9943	0.9932
LR+chi2	0.9982	0.9982	0.9963	0.9972
KNN	0.9976	0.9982	0.9967	0.9955
KNN+chi2	0.9996	0.9992	0.9997	0.9995
DT	0.9990	0.9975	0.9898	0.9796
DT+chi2	0.9998	0.9995	0.9998	0.9996
NB	0.9900	0.9778	0.9901	0.9819
NB+chi2	0.9902	0.9781	0.9921	0.9849
RF	0.9990	0.9985	0.9898	0.9976
RF+chi2	0.9997	0.9995	0.9998	0.9996
SVM	0.9969	0.9970	0.9963	0.9970
SVM+chi2	0.9989	0.9990	0.9975	0.9982

to prevent communication errors that could cause traffic disruptions or accidents between networks and interconnected vehicles. Development of IoV protection technologies and increased security investment. Ensuring security for vehicle exchange data storage and infrastructure. For the UDP Lag, DT, and RF models had the best results with a precision, recall, and F1 score of 99.9%. In the SYN flood attack, the best tested ML models appeared superior, with KNN, DT, and RF having the best results with 99.9% precision, recall, and F1score. This work opens the door to the development of many future endeavors. For example, optimizing ML models, analyzing features and their impact on different ML models, interpreting ratings, and assessing portability based on comparisons to other datasets.

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A Review on DDoS Attacks Classifying and Detection by ML/DL Models

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***Abstract*—Internet security is under serious threat due to Distributed Denial of Service (DDoS) attacks. These attacks inflict considerable damage by disrupting network services, resulting in the impairment and complete disablement of system functions. The accurate classification and detection of DDoS attacks is extremely important. We provide a review of different models of Machine Learning (ML)/Deep Learning (DL)-based DDoS attack detection used by researchers that consider different classifiers. Our analysis indicates a heightened emphasis on ML-based classifiers where 22% of studies opted for the widely recognized SVM classifier. For DL-based, 27% of the studies opted for the widely recognized CNN. While the majority of researchers have formulated their datasets, NSL-KDD was employed in 55% of the studies. In addition, we discussed the future directions and challenges of DDoS detection.**

***Keywords*—Classification; DDoS attacks; machine learning; cybersecurity; detection**

I. Introduction

Lately, there has been a noticeable surge in Distributed Denial of Service (DDoS) attacks, as attackers continually devise novel and sophisticated methods to carry out these assaults [1]. This initiates a denial-of-service attack concurrently, affecting a computer network simultaneously [2]. A DDoS attack achieves success by depleting the bandwidth, the processing capacity of routing devices, network or processing resources, memory, and database, as well as the input and output operations bandwidth of server systems [3],[4]. Preventive measures exist to counteract such attacks. Yet, it is crucial to recognize the distinctive traits of the attack to implement the most effective actions and prevent its reoccurrence [5]. Several prevalent forms of DDoS attacks include The Internet of Things (IoT), which refers to the integration of interconnected, internet-enabled objects capable of gathering and exchanging information through wireless networks without manual intervention [6]. Efficient techniques for identifying intrusions, including DoS attacks, SYN floods, and port scans. The exploration of this field has gained significant momentum as a subject of active research. Within the realm of flooding attacks, emphasis is placed on Flags—six distinct bits utilized to convey various conditions. The field of Machine Learning (ML) plays a crucial role in empowering organizations to make diverse decisions. Future classification and prediction can leverage the insights gained from all types of data. ML, an application of artificial intelligence, allows systems to autonomously comprehend and enhance their understanding without explicit programming. It focuses on refining computer programs that can independently absorb and learn from information. Utilizing supervised classification algorithms for categorical datasets is common in tasks involving classification and prediction, drawing upon existing knowledge and experience [7]. There are numerous ML algorithms, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees (DT), Genetic Algorithms (GA), kmeans, Apriori, AdaBoost, Cluster Analysis, Naïve Bayes (NB), PageRank, k-nearest neighbors, and PageRank.

A. DDoS Attacks

Throughout the years, a DDoS attack has posed a continuous security threat to online networks and services. The primary goal of DDoS attacks is to diminish service availability by depleting network or computational resources allocated for traffic and processing. As a result, legitimate users encounter obstacles when attempting to access the intended services [8]. A DDoS attack involves utilizing a vast array of compromised devices strategically dispersed globally within a botnet. This method contrasts with traditional DoS attacks, where a single network connection and one Internet-connected device are employed to inundate the target with malicious traffic [9].

B. How DDoS Attack Works

A DDoS attack can be initiated in various ways [10], with the most prevalent method involving the assailant sending a continuous stream of packets to the targeted server. Utilizing crucial resources in this manner creates challenges for genuine users attempting to access these resources. Another frequently employed strategy involves sending a small number of malformed packets, compelling the targeted servers to freeze or reboot. A different strategy for conducting a denial-of-service involves the deliberate sabotage of devices within the targeted network, depleting crucial resources and rendering the network inaccessible for both internal and external services. Numerous other methods exist for executing such attacks, making them challenging to anticipate and only identifiable after they have been initiated. Fig. 1 shows an example of a DDoS attack.

A DDoS attack unfolds through multiple stages involving three key entities: an assailant, a botnet, and a target. The assailant initiates the attack by dispatching remote instructions to each bot, orchestrating the inundation of connection requests exceeding the server's capacity. This method involves flooding the victim's server or network with copious amounts of random data, depleting the available bandwidth. As the botnet concentrates its efforts on the target's IP address, each bot sends requests, potentially overwhelming the server or network and causing a disruption in regular traffic, resulting in a service denial.

C. Types of DDoS Attacks

There are three types into which DDoS attacks can be classified. Firstly, there are volume-based attacks, where the

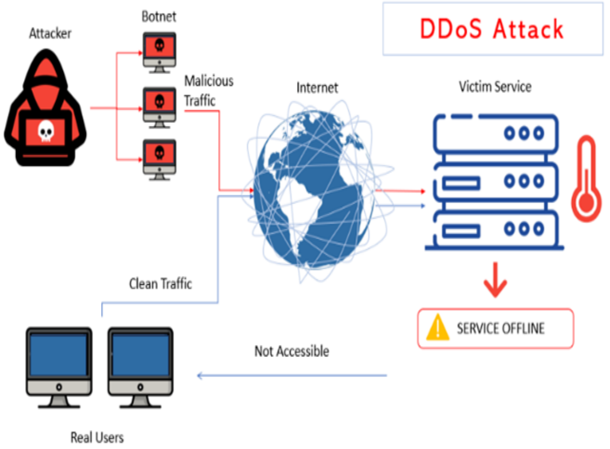
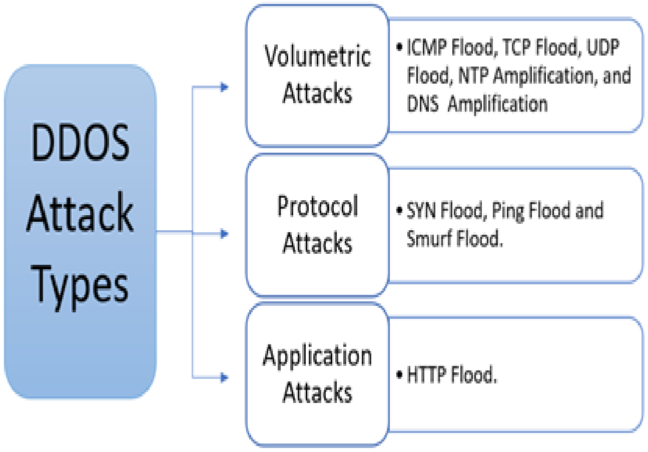


Fig. 1. Example of DDoS attacks.

aim is to overwhelm a target with a substantial amount of traffic, exploiting its bandwidth. Secondly, protocol-based attacks focus on exploiting vulnerabilities at layer 3 or layer 4, depleting the processing capabilities of the targeted system or critical resources like firewalls, leading to potential service interruptions. Lastly, application layer attacks involve connecting to a victim in a seemingly legitimate manner to exploit vulnerabilities at layer 7. These attacks utilize transactions and processes to overwhelm the server's resources excessively [11]. Fig. 2 shows the types of DDoS attacks with their examples.


DDOS Attack Types

Volumetric Attacks
- ICMP Flood, TCP Flood, UDP Flood, NTP Amplification, and DNS Amplification

Protocol Attacks
- SYN Flood, Ping Flood and Smurf Flood.

Application Attacks
- HTTP Flood.

Fig. 2. The types of DDoS attacks.

- Attacks involving SYN Flood: In the Transmission Control Protocol (TCP) protocol, the connection is formed through a three-way handshake, during which the server and client exchange synchronization (SYN) and acknowledgment (ACK) messages. SYN Flood attacks occur when a client sends an inaccurate ACK message, containing a forged IP address, in response to the server. Consequently, the server responds to the incorrect IP address with a SYN message and awaits a reply from the client. This waiting period renders the connection idle, preventing the server from catering to legitimate users. This type of attack is particularly susceptible due to its reliance on the vulnerabilities within the three-way handshake protocol [12].
- User Datagram Protocol (UDP) flood attacks: exploiting the characteristics of the UDP, which lacks the handshake process present in the TCP. In this type of attack, packets are directly sent to the target server, allowing the attacker to leverage this property to inundate the server with a significant volume of traffic. Consequently, the network resources of the target server become depleted due to the overwhelming volume of incoming data.
- HTTP flood attack: this is a cyber-attack in which the assailant exploits legitimate HTTP GET or POST requests to target a web application or server. Typically, these attacks leverage a botnet, which is a network of interconnected computers on the Internet.
- Ping of Death: Refers to an obsolete version of an Internet Control Message Protocol (ICMP) ping flood attack. In IPv4, the IP protocol imposes a maximum packet size of 65,535 bytes for communication between two devices. Exploiting this limitation through a basic ping command to transmit malformed or excessively large packets can result in significant harm to an unpatched system.
- SMURF attacks: involve the use of spoofed PING messages, causing a surge in ICMP requests upon pinging the targeted IP address. This influx of requests not only results in the consumption of significant bandwidth but also leads to a slowdown in the computer [13].
- Fraggle attack is a form of DDoS attack wherein a substantial volume of UDP traffic is employed to overwhelm the transmission infrastructure of the switch. It bears similarity to a Smurf attack, but distinguishes itself by utilizing UDP instead of ICMP [14].
- Network Time Protocol (NTP) amplification attack involves exploiting the features of an NTP server to overwhelm a target server or network with an extensive volume of UDP traffic. Consequently, this action renders the destination infrastructure inaccessible to normal, legitimate user traffic [15].

In this paper, Section II discusses the materials and methods through a literature survey and a description of various methods. Section III shows the classification tasks in ML and the ML algorithms performance metrics used to evaluate them. Section IV illustrates the discussion of the results. Open research directions will be presented in Section V. Finally, the last section briefly concludes our paper.

II. Literature Review

In recent times, numerous reports have indicated the occurrence of DDoS attacks targeting both commercial and government websites [16]. As the technique for executing DDoS attacks has advanced, the corresponding research on detection has also progressed. Consequently, numerous approaches have been proposed to mitigate DDoS attacks. In 1990, a proposal was made for a network traffic controller that utilizes ML techniques. The objective of this controller was to optimize call completion within a circuit-switched telecommunications network [17]. This work signified a pivotal moment when ML techniques broadened their scope to encompass the telecommunications networking domain. In 1994, ML was initially employed for classifying internet flow in intrusion detection. This marked the commencement of extensive research utilizing ML techniques in the classification of internet traffic [18]. In this section, we elaborate on recent advancements and developments related to the detection of DDoS attacks. Additionally, we provide insights into the deployments and data utilized to achieve the presented findings.

A. Machine Learning Approaches

Yusof et al. [19] utilized the KDD99 dataset for attack data and employed Information Gain to assess the significance of each feature, leading to the selection of relevant features. The WEKA tool was utilized for the classification of attacks and normal traffic. The proposed ML system by Yusof et al. [19] comprises various methods applied to the dataset. Their hybrid technique, a KNN-SVM method, is proposed for the classification, detection, and prediction of DDoS attacks. The methods employed by Yusof et al. include k-nearest neighbors (KNN), SVM, DT, K-means, NB, and Fuzzy c-means (FCM). Performance metrics such as True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN), and F-Measure were used by Yusof et al. [19]. Experimental results indicate that Fuzzy c-means clustering outperforms other algorithms in terms of classification accuracy and speed. Sanmorino, A. [20] utilized secondary data collected by other researchers in the development of the ML system. The proposed ML system comprises various methods applied to the acquired information, with a focus on evaluating the accuracy of each ML classification technique in identifying DDoS attacks. Sanmorino, A. applied three methods, namely the DT method, NB, and ANN, and assessed their performance using metrics such as True Positive (TP), False Positive (FP), Precision, Recall, F-Measure, and Receiver Operator Characteristic graphs/ Area Under the Curve (ROC/AUC). The findings indicate that, among the methods employed by Sanmorino, A. [20], the ANN demonstrated the highest accuracy compared to the other two methods for the generated dataset. Radivilova et al. [21] utilized the SNMP-MIB Dataset to investigate various types of attacks, including TCP SYN, UDP flood, ICMPECHO, HTTP flood, Slowpost, Slowloris, and SSH brute force. The study involved analyzing primary approaches for detecting DDoS attacks through the realization of network traffic. The results obtained from employing ML to detect DDoS attacks were presented, with input data comprising simulated realizations of both normal and attacked network traffic exhibiting fractal properties. The classification of traffic realizations took into account various parameters such as the Hurst index, attack type, and intensity. Experimentally, attack levels of 10%, 15%, 20%, and 20% were chosen, and the initiation moment and duration of the attacks were randomly selected. The training process was conducted separately for each attack file, employing the Random Forest (RF) method as applied by Radivilova et al. The results demonstrated that the most effective method employed by Radivilova et al. [21] for detecting attacks in network traffic is RF. Nandi et al. [22] proposed a hybrid approach aimed at identifying top relevant features through the utilization of both established feature selection methods and hybrid techniques on the NSL KDD dataset. The procedure entailed employing five feature selection methods, namely Information Gain, Gain Ratio, Chi-squared, Relief, and Symmetrical Uncertainty, to identify the most pertinent features within the NSL KDD dataset. Subsequently, a hybrid feature selection method was applied to further refine the feature set, selecting the most crucial features. The dataset was then filtered to isolate DDoS packets using the chosen features, as not all anomalous instances in the dataset belonged to the DDoS category. Nandi et al. employed various methods, including NB, Bayes Net, Decision Table, J48, and RF, and their results indicated that the hybrid approach demonstrated superior detection rates compared to existing methods. In their study, Bagyalakshmi et al. [23] introduced two approaches utilizing a dataset sourced from NSL-KDD. The first approach employs Learning Vector Quantization (LVQ) as a filter method, while the second approach utilizes Principal Component Analysis (PCA) as a dimensionality reduction method. Features selected from each approach are employed in the classification process, and the outcomes are compared in relation to their effectiveness in detecting DDoS attacks. Bagyalakshmi et al. applied NB, SVM, and DT as classification methods. The findings presented by Bagyalakshmi et al. [23] indicate that the LVQ-based DT technique outperforms the others in terms of identifying attacks. In their work, Sahoo et al. [24] employed an SVM with kernel principal component analysis (KPCA) for feature selection, while a GA algorithm was utilized to optimize the SVM parameters. To address the issue of noise arising from feature variations, they introduced an enhanced kernel function (N-RBF). Sahoo et al. [24] chose SVM as the primary classifier for predicting malicious traffic, presenting an effective solution for securing Software-Defined Networking (SDN). Their proposed approach integrates SVM with KPCA and GA, using KPCA for feature extraction and SVM for attack classification. To reduce training time, they introduced an improved radial basis kernel function. The optimization of various classifier parameters was achieved through the application of a GA algorithm. The detection module was executed on the controller, and the proposed DDoS detection framework was validated in a simulated environment involving a POX controller, Open vSwitch (OVS), and Mininet emulator. Comparative analysis with other classifiers from [24] revealed that the SVM model they proposed exhibited superior effectiveness and accuracy in classification for attack detection. Chartuni et al. [2] introduced a methodology that centers around the exploration and selection of a dataset representing DDoS attack events. This involves preprocessing the data and creating a sequential neural network model for multi-class classification, utilizing the CIC DDoS2019 dataset. The approach is specifically focused on multi-classification. They highlighted the enhanced value of multi-class classification in comparison to binary classifications, contrasting their models with those presented previously. Their utilized method involves Dense Neural Networks (DNN). The model proposed by Chartuni et al. demonstrated notable performance, achieving approximately 94% in metrics such as $precision$, $accuracy$, $recall$, and $F1-score$. Jaiswar, R. [25] employed the CICIDS 2017 dataset for the attack data in their study. The model was built using correlation analysis to choose relevant features and diminish the dataset's dimensionality. Following that, K-Means Clustering was utilized on a dataset with selected features to produce clusters, subsequently designated as either Benign or Attack. The labeled clustered dataset was fed into an SVM for training and testing the model. Jaiswar, R. utilized an SVM. The findings indicate that Jaiswar, R.'s model successfully categorizes web traffic based on its nature (Benign or Attack traffic). Upon evaluation, the model demonstrated superior performance compared to other classification algorithms tested on the available dataset. Aamir et al. [26] proposed a framework comprising four key stages: dataset acquisition, feature engineering, evaluation of the machine learning (ML) model, and analysis of results. The acquisition of the dataset involves a systematic exploration of published and validated datasets that contain evidence of DDoS attacks. Feature engineering follows dataset selection and entails analyzing the dataset to understand its context, identifying duplication and collinearity among attributes, and making adjustments to render it suitable for training the chosen ML model. The model evaluation process encompasses initial training, fine-tuning hyperparameters based on results, and assessing the modified model. Aamir et al. [26] assessed five ML models—SVM, RF, ANN, NB, and K nearest neighbors (KNN). The classification results indicate that all variants of discriminant analysis and SVM demonstrate good testing accuracy. Ismail et al. [27] employed the UNWS-np-15 dataset, utilizing RF and XGBoost classification algorithms. Following the application of these ML models, a confusion matrix was generated to assess model performance. The findings indicated that XGBoost outperformed other models in terms of precision, making it the preferred choice for the dataset used by Ismail et al. [27].

Kareem et al. [28] conducted an assessment of the efficiency of rapid ML techniques for model testing and generation within communication networks, with a focus on identifying denial-of-service attacks. The CICIDS2017 dataset in the WEKA tool served as the training and testing ground for multiple ML algorithms. The evaluated methods included REP tree (REPT), random tree (RT), RF, decision stump (DS), and J48. Performance metrics such as $accuracy$, $F-score$, $precision$, and $recall$ were employed by Kareem et al. [28]. Their experiments revealed that J48 exhibited superior performance and quicker testing times, especially when utilizing 4-8 features. Alduailij et al. [29] conducted research with the primary objective of enhancing the performance in detecting DDoS attacks. The study involved experiments using the CICIDS 2017 and CICDDoS 2019 datasets. Alduailij et al. [29] employed Mutual Information (MI) and RF Feature Importance (RFFI) methods for their investigation. The methodology utilized by Alduailij et al. [29] encompassed RF, Gradient Boosting (GB), Weighted Voting Ensemble (WVE), K Nearest Neighbor (KNN), and Logistic Regression (LR). The evaluation of their approach was based on performance metrics such as $Precision$, $recall$, $F-score$, and $accuracy$. According to the experimental results, the accuracy achieved by RF, GB, WVE, and KNN with 19 features was 0.99. Table I summarizes previous studies focused on utilizing machine learning methodologies for the identification of DDoS attacks.

Classification algorithms are employed to discern DDoS attacks by classifying traffic packets. Various ML algorithms, including SVMs, ANNs, DT, GA, AdaBoost, k-means, Apriori, k-nearest neighbors, Cluster Analysis, PageRank, and NB, can be utilized for this purpose.

B. Deep Learning Approaches

Numerous DL techniques have been proposed to classify and predict Distributed Denial of Service (DDoS) attacks. Yuan et al. [30] present a DL-based approach for detecting DDoS attacks, wherein high-level features are automatically derived from low-level ones, producing a resilient representation with enhanced inference capabilities. They construct a recurrent deep neural network to identify patterns within sequences of network traffic, enabling the tracking of activities associated with network attacks. Yuan et al. [30] showcased favorable results, demonstrating a significant decrease in the error rate from 7.517

Li et al. [31] underscore the superiority of DL in comparison to traditional DL techniques for detecting DDoS attacks. They introduces a detection model and defense system rooted in DL within a Software-Defined Network framework. The experimental findings highlight the model's significantly improved performance when contrasted with conventional ML approaches. Furthermore, it diminishes reliance on the environment, streamlining real-time updates to the detection system, and easing the challenges associated with upgrading or altering the detection strategy.

In their study, Alguliyev et el. [32] presented an approach for anticipating the onset of DDoS attacks through the identification of pertinent content in social media. They employ a CNN model featuring 13 layers and an enhanced LSTM method to achieve precise classification of texts into positive and negative categories. The prediction of DDoS attacks occurring the following day relies on analyzing the negative and positive sentiments within social media texts. The effectiveness of their proposed method was assessed through experiments conducted on Twitter data.

Shurman et al. [33] introduced two approaches for identifying Distributed Reflection Denial of Service (DDoS) attacks in the context of the IoT. The initial method employs a hybrid Intrusion Detection System (IDS) designed to identify IoT-DoS attacks, while the second method utilizes DL models built on Long Short-Term Memory (LSTM), trained with the most recent dataset specifically tailored for DrDoS incidents. Shurman et al's experimental findings illustrate that implementing these methodologies effectively detects malicious activities, thereby enhancing the security of IoT networks against both Denial of Service (DOS) and DDoS attacks.

Cil et al [34] proposed the utilization of a deep neural network (DNN) as a DL model for detecting DDoS attacks. Employing the CICDDoS2019 dataset in their experiments, they observed a remarkable 99.99% success rate in detecting DDoS attacks on network traffic. Additionally, the classification of attack types achieved an accuracy rate of 94.57% based on the dataset.

In [35], they conducted traffic classification on Software-Defined Network (SDN) traffic provided by Leading India. They employed diverse DL approaches to categorize the traffic into either normal or malicious classes. The findings of Ahuja et al. [36] demonstrated remarkable success, achieving an impressive accuracy rate of 99.75% through the utilization of Stacked Auto-Encoder Multi-layer Perceptron (SAE-MLP).

Agarwal et al. [36] introduced a deep neural network-

TABLE I. Summary of MLbased Research Papers

Ref.	Performance Metrics	Dataset	Contribution	Approach	Year
[19]	TP, FP, TN, FN, F-Measure.	KDD99	A hybrid method for classifying, detecting, and predicting the DDoS attack by ML.	SVM, k-nearest neighbor, K-Mean, NB, Fuzzy C Mean	2016
[20]	TTP, FP, Precision, Recall, F-Measure, ROC / AUC	Bank Data Classification of the DDOS attack by ML	DT, NB	ANN	2019
[21]	TP, FN, Accuracy.	SNMP-MIB	Classification by using fractal and recurrence features.	RF	2019
[22]	k-fold cross validation	NSL-KDD	Detection and classification of the DDoS attacking packets and normal packets.	NB, Bayes Net, Decision Table, J48, and RF	2020
[23]	Accuracy, Precision, Recall, Specificity, F-Measure	NSL-KDD	Intrusion detection for DDoS attacks cloud environment	DT, NB, SVM	2020
[24]	TP, FP, TN, FN, FMeasure.	NSLKDD, KDD	Classification of DDoS attacks SVM	GA	2020
[25]	Accuracy, Precision, Recall, F1 Score.	CICDDoS2019	Multi-class classification of the DDoS attack	Dense Neural Networks	2021
[26]	Accuracy, FP.	CICIDS 2017	Identify and classify DDoS attack	SVM	2021
[27]	k-fold cross validation	CICIDS 2017	classification of DDoS attacks	SVM	2021
[28]	Accuracy, Precision, Recall, F1 Score.	UNSW-nb15	Detection of the DDOS attack	RF, XGBoost.	2022
[29]	Accuracy, F-score, Precision, and Recall.	CICIDS 2017	Classification of DDoS attacks	REP Tree, Random Tree, RF, Decision Stump, J48.	2022
[30]	Precision, Recall, F-measure, and Accuracy.	CICIDS 2017 and CICD-DoS 2019	Classification of DDoS attacks	RF, Gradient Boosting, Weighted Voting Ensemble, K-Nearest Neighbor, LR	2022

based feature selection-whale optimization algorithm (FS-WOA–DNN) for distinguishing between normal and attacked data. The chosen features undergo classification through a deep neural network classifier, utilizing the CICIDS 2017 dataset. The algorithm's performance was evaluated through simulation using the MATLAB tool, demonstrating an experimental accuracy of 95.35% in detecting DDoS attacks.

In their work, Reddy et al. [37] proposed a hybrid neural network structure that integrates a Gradient Boosting DT with a nimble Convolutional Neural Network (CNN). The results from these models are unified through an additive function to merge spatial and temporal characteristics, yielding a hybrid model proficient in differentiating between malicious and benign ultimate traffic flow. The hybrid ensemble learning model, as presented by Reddy et al, showcased enhanced accuracy compared to established detection methods. Boonchai et al. [38] proposed models leveraging deep neural networks designed for efficient multiclass classification of DDoS, utilizing the CICDDoS2019 dataset. They have introduced two models employing a straightforward DNN architecture and a Convolutional Autoencoder. The authors demonstrated enhanced classification accuracy through the application of DL techniques, achieving an accuracy of 91.9

Guo et al. [39] presented GLD-Net, a DL approach that combines topological and traffic features to achieve high accuracy in detecting DDoS attacks. These investigations collectively illustrate the effectiveness of DL in accurately categorizing DDoS attacks. Experiments conducted on the NSL-KDD2009 and CIC-IDS2017 datasets reveal that GLD-Net achieves detection accuracies of 99.3% for two classifications (normal and DDoS flow) and 94.2% for three classifications (normal, fast DDoS flow, and slow DDoS flow). Table II summarizes the papers that use DL approaches to detect DDoS assaults.

III. Classifications, Dataset and Performance metrics

A. Classificaton Methods

In classification tasks, the objective is to anticipate the output variable by analyzing the input features provided. The output varies across different tasks. Several frequently common classification tasks include:

- Binary Classification: involves a target variable with two possible outcomes, usually denoted as 0 or 1. Applications of this classification type include spam detection, fraud detection, and disease diagnosis. A range of studies have successfully applied ML to the binary classification of DDoS attacks. Bakhareva et al. [40] present algorithms designed to identify attacks within enterprise networks by analyzing network traffic. To assess ML methods for binary classification (distinguishing between attack and regular traffic) and multiclass classification (identifying various classes of typical attacks), the researchers utilized the CICIDS2017 dataset. The findings indicated that the CatBoost and LightGBM algorithms demonstrated effective performance in both binary and multiclass classification, successfully categorizing malicious traffic into distinct attack groups.
- Multi-class Classification involves scenarios where the target variable can have more than two potential outcomes, usually denoted as unique labels or classes. Numerous studies have investigated the application of ML in the multi-classification of DDoS attacks. In their work, Sayed et al. [41] introduced a multi-classifier model based on a stacking ensemble deep neural network. This model effectively identifies various types of DDoS attacks, achieving an accuracy rate of 89.4% when evaluated on the CIC-DDoS2019 dataset. Parfenov et al. [42] expanded the feature set for detecting attacks through the application of ML techniques. They explored methods for binary and

TABLE II. SUMMARY OF DLBASED RESEARCH PAPERS

Ref.	Performance Metrics	Dataset	Contribution	Approach	Year
[36]	Error Rate, Accuracy, Precision, Recall, F1, AUC.	ISCX2012	Classification DDOS Attacks by DL	CNN, RNN, LSTM, and GRU.	2017
[37]	Accuracy, Precision, F1 Score.	ISCX2012	Detection and defense system from the DDoS attack by DL in SDN environment.	RNN, LSTM, and CNN.	2018
[38]	Recall, Precision, F-measure, Training loss, Training accuracy, Testing loss, and Test accuracy.	Data collected from social media	Predicts DDoS attack occurrence by finding relevant texts in social media.	CNN, and LSTM.	2019
[39]	TP, FP, TN, FN	CICDDoS2019	DDoS attacks Detection in IoT.	RNN, and LSTM.	2020
[40]	TP, FP, TN, FN	CICDDoS2019	Detection of DDoS attacks on the packets captured from network traffic.	DNN	2021
[41]	Accuracy, Precision, Recall, F-score, False positive rate, and False negative rate.	Dataset provided by leadingindia.ai.	Detection of DDOS Attack on software-defined networking traffic.	CNN, LSTM, CNN-LSTM, SVC-SOM, SAE-MLP.	2021
[42]	Accuracy, Sensitivity, Specificity, Error, False Positive Rate (FPR), False Negative Rate (FNR), Positive Predictive Value (PPV), and Negative predictive value (NPV).	CIC-IDS 2017	Detection of DDOS Attack Using DL Model in Cloud Storage Application.	SVM, KNN, ANN, DNN and FS-WOA–DNN.	2021
[43]	Accuracy, Precision, Recall, F-measure.	CICDDoS2019	Detection of DDOS Attack Using DL	GBDT, CNN.	2021
[44]	Accuracy, Precision, Recall, F-1score.	CICDDoS2019	classification of DDoS attacks Using DL	DNN	2022
[45]	TP, FP, TN, FN NSL-KDD2009	CIC-IDS2017	Detection of DDoS Attacks via Topological and Traffic Feature Fusion using DL.	GLD-Net, DT, RF, Stacked-DNN, FastGRNN, FastGRNN.	2022

multiclass classification of network traffic to identify potential attack patterns. Additionally, a comparative analysis was conducted on ML algorithms including Gradient Boosting, AdaBoost, and CatBoost, utilizing the CICDDoS2019 dataset. The findings revealed that CatBoost demonstrated superior performance in both binary and multiclass classification, achieving accuracies of 99.3% and 97%, respectively. In their study, Mungwarakarama et al. [43] applied an Optimized K-Nearest Neighbor (OKNN) model to a real network dataset. By tuning parameters such as $n_neighbors$, $metrics$, $weights$, and n_jobs, the model demonstrated a notable proficiency in accurately distinguishing between normal traffic flow and DDoS attacks. The experimental outcomes showcased a high level of accuracy in the identification of both normal traffic and DDoS attacks.

- Hierarchical Classification: This classification method involves a target variable with a hierarchical or nested arrangement, where classes are structured in a tree-like form. Instances of hierarchical classification can be observed in species classification and product categorization. Various ML techniques have been suggested for the hierarchical classification of DDoS attacks. In their study, Kang et al. [44] presented a taxonomy that relies on similarity and hierarchical clustering to categorize 12 real DDoS attack tools. The effectiveness of this taxonomy was assessed, revealing its capability to accurately classify complex attack instances. Table III summarizes the papers on classification Tasks in ML approaches.

TABLE III. SUMMARY OF CLASSIFICATION TASKS ML-BASED RESEARCH PAPERS

Ref.	Classification Tasks	Approach	Dataset
[30]	Binary Classification	CatBoost, LightGBM.	CICIDS2017
[31]	Multi-class Classification	Convolution Neural Networks (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU).	CIC-DDoS2019
[32]	Multi-class Classification	Gradient Boosting, AdaBoost, and CatBoost	CICDDoS2019
[33]	Multi-class Classification	Optimized K-Nearest Neighbor (OKNN)	LRN
[34]	Hierarchical Classification	Characteristic tree, and Hierarchical Clustering.	

B. Available Benchmarked DDoS Datasets

The studies analyzed for DDoS attack detection employed datasets listed in Tables I, II, and III, which were commonly utilized across most of the studies. The subsequent section provides descriptions of these datasets: The NSL-KDD dataset: Is an enhanced version of the KDD Cup99 dataset, where several fundamental issues have been addressed and rectified through modifications and removals. Comprising 41 features, this dataset categorizes attacks into four groups [45]. ISCX2012: This dataset, created in 2012 by Ali Shiravi and colleagues, encompasses a comprehensive collection of network data. It spans seven days, specifically from June 11 to June 17, 2010, capturing a spectrum of network activities, ranging from legitimate to malicious traffic. Examples of malicious activities within the dataset include DDoS, HTTP Denial of Service, and Brute Force SSH. Formulated within the framework of a simulated network environment, this dataset comprises both sorted and unbalanced data. It employs two overarching profiles: one delineates attack patterns, while the other characterizes typical user scenarios within the ISCX dataset [46]. UNSW-NB15: This dataset was produced by the Australian Center for Cyber Security. Generated the UNSW-NB15 dataset, employing Bro-IDS and Argus tools alongside several newly developed methods. The dataset comprises around two million records featuring a total of 49 characteristics. It encompasses various attack types [47]. CICIDS 2017: This was generated by the Canadian Institute for Cybersecurity (CIC) in the year 2017. It encompasses a variety of real-time attacks as well as typical network flows. CIC Flow Meter utilizes information derived from logs, source and destination IP addresses, protocols, and identified attacks to assess network traffic [48]. CICIDS 2017 encompasses common attack scenarios, including but not limited to brute force attacks, HeartBleed attacks, botnets, DDoS, DoS, web attacks, and exfiltration attacks [49]. CSE-CIC-IDS2018: In 2018, a collaboration between the Communications Security Foundation (CSE) and CIC resulted in the development of the CSE-CIC-IDS2018 dataset. This dataset was constructed by generating user profiles containing abstract descriptions of various events, which were subsequently amalgamated with a distinctive set of attributes. The dataset encompasses seven different attack scenarios, such as Brute Force, Heartbleed, Botnet, DoS, DDoS, web attacks, and insider network compromise [50]. CICDoS2019: This dataset created by Sharafeldin et al. [51] in 2019, was generated by extracting over 80 traffic features from the original data using the CICFlowMeter-V3 feature extraction software. Table IV summarizes the Datasets and their features.

TABLE IV. SUMMARY OF DATASETS AND FEATURES

Ref.	Dataset	Attacks	Features
[45]	NSL-KDD	4	41
[46]	ISCX2012	6	-
[47]	UNSW-NB15	9	43
[48]	CICIDS 2017	14	77
[50]	CSE-CIC-IDS2018	7	80
[51]	CICDoS2019	13	88

C. Performance Metrics

Performance metrics used in studies to detect DDoS attacks are listed, with a focus on performance indicators as the predominant measures. In binary classification scenarios, common metrics encompass $Precision$, $recall$, $F1_score$, and area under the curve, among others. The confusion matrix serves as a comprehensive summary of the classification model's predictions, incorporating True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) [52]. Eq. (1) defines the true positive rate (TPR), which is alternatively referred to as recall or sensitivity [53]. The TPR should be as high as possible.

$$recall = \frac{TP}{TP + FN} \tag{1}$$

The Precision of the model is determined using Eq. (2), which involves checking the number of correctly predicted positive classes by the model that are truly positive instances.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Eq. (3) presents the false positive rate (FPR), which quantifies the proportion of negative occurrences that the model erroneously identifies as positive.

$$FPR = \frac{FP}{TN + FP} \tag{3}$$

The false negative rate (FNR) is the percentage of positive cases wrongly identified as negative. It is calculated using Eq. (4).

$$FNR = \frac{FN}{TP + FN} \tag{4}$$

Eq. (5) illustrates the TNR, also known as Privacy, representing the percentage of accurately predicted negative as negative.

$$TNR = \frac{TN}{TN + FP} \tag{5}$$

In Eq. (6), $accuracy$ is characterized as the proportion of true predictions made by the model across all classes. A preference is given to achieving the highest level.

$$Accuracy = \frac{TP + TN}{Total} \tag{6}$$

Comparing two models becomes challenging when one exhibits high $recall$ and low precision, or vice versa. To address this issue, the $F1 - score$ is employed as a metric for comparison, providing a balanced evaluation of both memory and accuracy. Eq. (7) is utilized for the calculation of the $F1 - score$.

$$F1 - Score = \frac{2 * Recall * Precision}{Recall + Precision} \tag{7}$$

The AUC-ROC curve measures the efficiency of classification problems at various threshold levels. A model is considered to offer more accurate predictions when the area under the curve approaches 1.

IV. DISCUSSION AND ANALYSIS

Detecting DDoS attacks with varying rates and patterns from legitimate traffic poses a significant challenge. Numerous ML/DL techniques have been suggested by researchers to identify DDoS attacks over the years. However, the effectiveness of these methods is constrained due to attackers consistently evolving their strategies and rapidly enhancing their skills, enabling them to execute unknown DDoS or zero-day attacks characterized by distinctive traffic patterns. Our analysis of prevailing classification methods centers on various aspects, such as the commonly employed classifiers and their influence on classification accuracy, as well as the datasets utilized for testing purposes. Researchers employed various ML classifiers in their methodologies, encompassing SVM, KNN, NB, DT, ANN, RF, J48, GA, LR, CatBoost, AdaBoost, and XGBoost. Among these, 22% of studies opted for the widely recognized SVM classifier, 10% employed the KNN classifier, 13% utilized the NB classifier, 9% applied the DT classifier, 6% implemented the ANN classifier, 16% employed the RF dataset, 3% each utilized the J48, GA, LR, CatBoost,

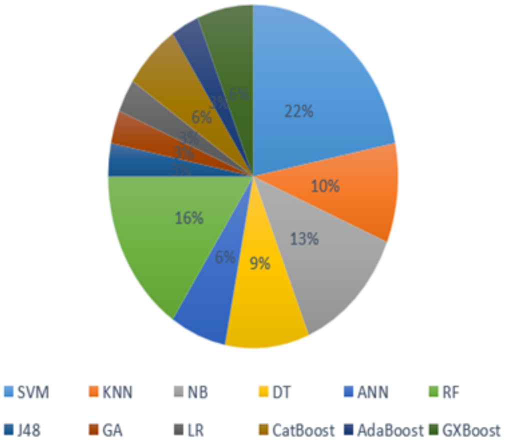


Fig. 3. Classification methods of ML approaches.

AdaBoost, and XGBoost classifiers. Fig. 3 illustrates ML classification methods in the studies.

In recent years, our observations indicate a heightened emphasis on ML-based classifiers. Specifically, in 2021, the SVM classifier took precedence, followed by the RF classifier in 2022, and the NB classifier in 2020, as illustrated in Fig. 4.

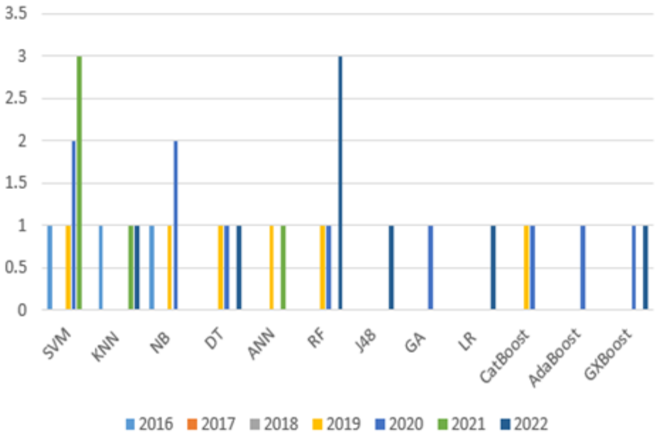


Fig. 4. Classification methods of ML approaches during past years.

The researchers have employed various DL classifiers, such as CNN, RNN, DNN, LSTM, GBDT, and GRU. Notably, 27% of the studies opted for the widely recognized CNN, while 14% utilized RNN, 18% employed DNN, 27% incorporated LSTM, 5% implemented GBDT, and 9% utilized GRU. Fig. 5 visually illustrates the distribution of DL classification methods in the research approaches.

Our analysis indicates that many researchers have formulated their datasets. In various studies conducted over recent years, several researchers employed widely recognized standard datasets, including KDDCUP99, NSL-KDD, UNSW-NB15, CIC-IDS2017, CSE-CIC-IDS2018, ISCX2012, and CICDDoS2019 in most of the studies over the past years, as Fig. 6.

Among the frequently utilized datasets in the literature, NSL-KDD was employed in 55% of the studies, UNSW-NB15 in 28%, KDDCUP99 in 6%, CIC-IDS2017 in 4%, CICDDoS2019 in 5%, CSE-CIC-IDS2018 in 1%, and ISCX2012 in 1%. Fig. 7 presents the distribution of different datasets used for classification.

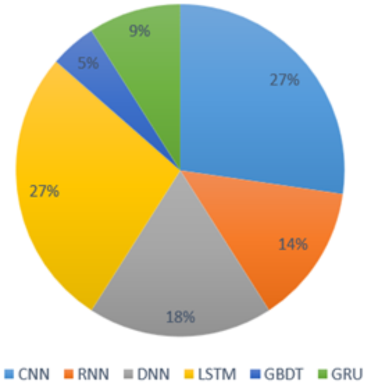


Fig. 5. Classification methods of DL approaches.

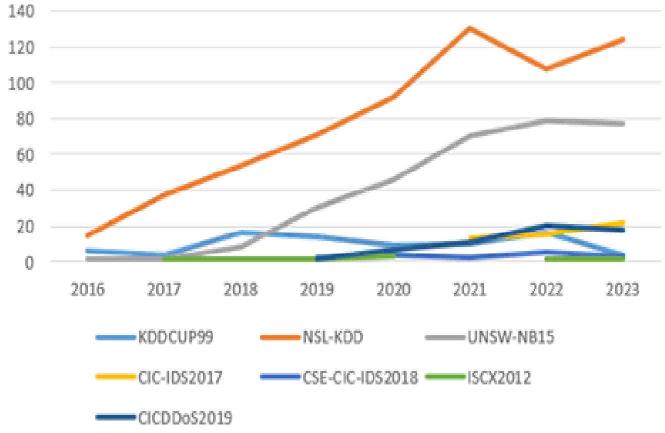


Fig. 6. Dataset that has been used over the past years.

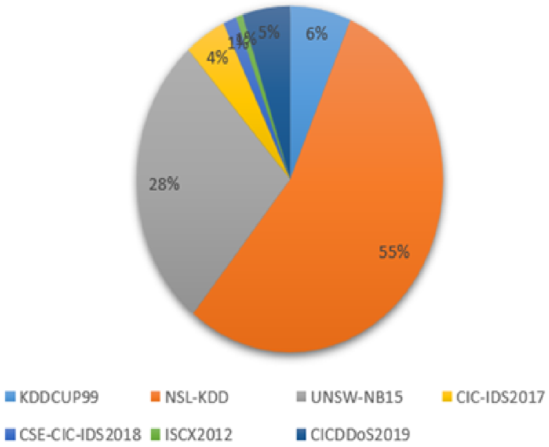


Fig. 7. The different datasets for classification methods.

V. Future Directions

The DDoS detection future research includes using advanced and improved DDoS mitigation techniques as follows:

- ML/DL Models: DL/ML models continue to be used to detect signs of DDoS attacks or analyze behaviors to detect anomalies. In addition to the possibility of mitigating its effects.
- Blockchain Technology: Using blockchain technology to detect DDoS, reducing its effects, and adopting it to raise trust between various entities and facilitate the safe exchange of information.
- Edge and fog computing: Use DDoS detection methods at the network edge to speed up response time. As for fog computing, it will be used to quickly distribute detection tasks and reduce risks.
- Human-centred approach: Develop DDoS detection interfaces based on user experience to increase user effectiveness and integrate experience into decision-making processes, especially when facing DDoS attacks.
- Quantum computing: With the advent of quantum computing, which is thought to break current algorithms, we need to develop DDoS detection techniques, and here quantum-resistant encryption methods must be used.

Continuing research and leveraging AI technologies is crucial to reducing DDoS threats. In addition, the combination of modern technologies and human expertise has a promising future for DDoS detection and reduction.

VI. Conclusion

Differentiating between DDoS attacks exhibiting various rates and patterns and regular traffic poses a considerable challenge. Numerous ML/DL approaches for detecting such attacks have been suggested by various researchers over the years. However, the constant evolution of attackers' tactics significantly restricts the effectiveness of these techniques. This paper provides a summary of the literature, adhering to the recommended taxonomy for DDoS attack detection through ML/DL methods. Our analysis indicates a heightened emphasis on ML-based classifiers where 22% of studies opted for the widely recognized SVM classifier. For DL-based, 27% of the studies opted for the widely recognized CNN. While the majority of researchers have formulated their datasets, NSL-KDD was employed in 55% of the studies. By addressing these future research areas, the field of DDoS detection can evolve to better cope with the increasingly sophisticated nature of cyber threats. Continuous research, and innovation will be key in staying ahead of evolving DDoS attack techniques.

Acknowledgment

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TPMN: Texture Prior-Aware Multi-Level Feature Fusion Network for Corrugated Cardboard Parcels Defect Detection

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***Abstract*—Surface defect detection is the task of identifying and localizing defects on the surface of an object, which is a widely applied task in various industries. In the logistics industry, logistics companies need to monitor the condition of goods for potential defects throughout the entire logistics process for effective logistics quality control. However, effective defect detection methods are still lacking for courier packages using corrugated cardboard boxes, which rely on judging whether deformation and leakage have occurred by examining areas on their surface with abundant texture. Specifically, the defect rate and supporting structure of the packages are influenced by temperature and humidity, and the openings and bends of defects are inconsistent. This results in defective packages having rich and non-uniform texture features. Moreover, convolutional neural networks struggle to effectively extract low-level semantic texture features of defects and perceive multi-level image features of packages. Considering the above challenges, we propose a novel texture prior-aware multi-level feature fusion network (TPMN). We first introduce prior knowledge and attention mechanisms to enable the neural network to focus on extracting low-level texture features from the image in the early stages. We also design a multi-level feature fusion method to integrate features from different levels, avoiding the gradual loss of low-level semantic information in CNN and enabling comprehensive perception of multi-level image features. To support further research, we contribute the cardboard-boxes-dataset, comprising 1210 images of packages. Experiments on this dataset showcase the superior performance of TPMN, even in few-shot learning scenarios, demonstrating its effectiveness in surface defect detection within the logistics and supply chain domains.**

Keywords—logistics; surface defect detection; multi-level feature fusion; prior attention; corrugated cardboard boxes

I. Introduction

Surface defect detection is a widely applied task in various industries, the goal of which is to identify and locate defects on the surface of objects. Nowadays, an increasing number of surface defect detection methods based on deep learning are being proposed. Lv et al. proposed a single shot multiBox detector-based end-to-end defect detection network for defects on metal surfaces [1]. Huang et al. proposed a method for defect detection in micro-nozzles using canny edge detection and evaluating the texture features of the regions [2]. Many mature methods have also been proposed for applications in other materials, such as steel strips [3], fabric [4], and solar cells [5].

Nevertheless, the logistics industry, which is rapidly developing alongside e-commerce, still lacks reliable methods for surface defect detection. Reliable courier packaging is crucial for logistics quality, especially for fragile items, and tracking courier parcel defect helps logistics companies determine responsibility and improve logistics quality control. However, the corrugated cardboard boxes used for courier packaging differ from other industrial materials as they have limited waterproof properties and compressive strength. It may suffer different degrees of defect in the logistics environment. Corrugated cardboard boxes are highly sensitive to atmospheric conditions, and the defect rate and structural support of the packages can be significantly affected by temperature and humidity [6], [7]. Meanwhile, under the pressure of other goods, corrugated cardboard boxes may also develop inconsistent sizes of openings [8] and bends [9], leading to damage to the cargo. This complex defect scenario renders traditional surface defect detection methods unsuitable for courier parcels. Therefore, logistics companies urgently need a comprehensive and reliable defect detection method to achieve precise detection of

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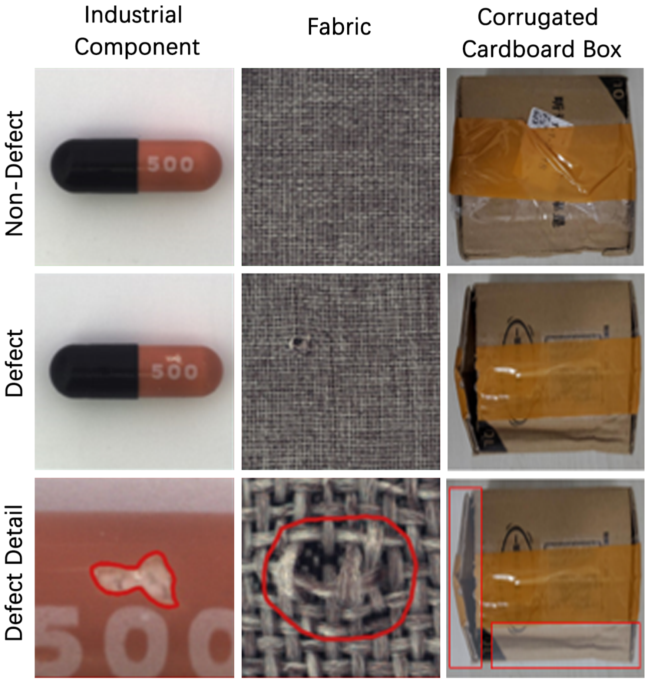


Fig. 1. Surface defects in different materials. In human judgment of whether a corrugated cardboard box has deformed or is leaking, it is typically reliant on image regions rich in textures, such as uneven package edges, folds extending around due to indentation, and edges at defect locations.

courier parcels, especially in cases with significant differences in defect sizes and overall structural. However, we still face the following challenges.

Firstly, the features of datasets for different defect detection tasks vary significantly, and the optimal solutions also differ. For corrugated cardboard boxes, humans judge whether deformation and leakage have occurred by examining areas on the surface with abundant texture (e.g., uneven package edges, depressed folds, defect edges). However, these texture-related low-level semantic features are often overlooked by Convolutional Neural Network (CNN) during the feature extraction process [10]. Additionally, low-level texture features suffer from semantic ambiguity due to their small receptive fields [11], [12]. Therefore, when analyzing the overall image and semantics of corrugated cardboard boxes, it is difficult to extract low-level texture image features.

Secondly, traditional methods often use the last convolutional feature map [13], resulting in insufficient semantic information and the loss of local information in the image. Specifically, courier parcels vary in size, and there is inconsistency in the texture sizes of corrugated cardboard boxes. When employing CNN with multiple convolution layers, local texture information may gradually be lost [14]. Moreover, in large-scale images, CNNs pay more attention to the high-level semantic information of the image [15], such as the overall structure and shape of corrugated cardboard boxes. Therefore, it is difficult to capture multi-level image features, which limits the task of surface defect detection on corrugated cardboard boxes.

In this paper, considering the above challenges, we propose a texture prior-aware multi-level feature fusion network (TPMN). Our method aims to accurately detect defect courier parcels, meeting the logistics company's need to track packaging defect status and providing crucial information for determine responsibility and improving logistics processes. Specifically, we first introduce prior knowledge and attention mechanisms to enable the neural network to focus on extracting low-level texture features from the image in the early stages. Then, we designed a multi-level feature fusion method to integrate features from different levels, avoiding the gradual loss of low-level semantic information in CNN and enabling comprehensive perception of multi-level image features. Additionally, we have contributed a dataset that comprises 1210 images of packages, known as the cardboard-boxes-dataset. On this dataset, we conducted basic experiments, ablation experiments, and few-shot learning experiments, among others. The experimental results demonstrate the superior performance of the TPMN.

To summarize, the primary contributions of this paper are as follows:

- We design the Texture Prior-Aware Multi-Level Feature Fusion Network, which integrates ResNet-18 [16] with multi-scale feature fusion and a prior attention mechanism. This framework enables precise defect classification and localization.
- The proposed TPMN is model-agnostic, allowing for effective extraction and fusion of low-level texture features while comprehensively perceiving multiscale image information.
- We released the Cardboard-Boxes-Dataset, which can be used for the task of detecting express packaging defects and promote further research in this field. The dataset is publicly available at https://github.com/chanllon/corrugated-cardboard-boxes-dataset.

II. Related Work

This section provides an overview of related work in three key fields: surface defect detection, prior attention, and multi-level feature fusion.

A. *Surface Defect Detection*

Surface defect detection is a widely applied task in various industries, with the main goal of identifying and locating defects or flaws on the surface of objects. Before the development of deep learning, surface defect detection primarily utilized traditional image processing techniques to extract features, employing machine learning for classification. Sun et al. utilized learning vector quantization networks and backpropagation networks for classification after segmenting the images [17]. Borwankar et al. introduced an k-nearest neighbors based algorithm for cast iron rocker arm inspection using frequency domain image processing [18]. However, these methods fall short in achieving superior detection accuracy. With the development of deep learning (DL), there are also many DL-based methods utilized for surface defect detection in the industry. Schlüter et al. introduce a simple and intuitive self-supervised method for sub-image anomaly detection and localization [19]. Lv et al. proposed a single shot multiBox detector-based end-to-end defect detection network for defects on the metal surface [1]. Huang et al. proposed a method using canny edge detection and evaluating region texture features for the defect detection of micro-nozzles [2]. Fang et al. designed

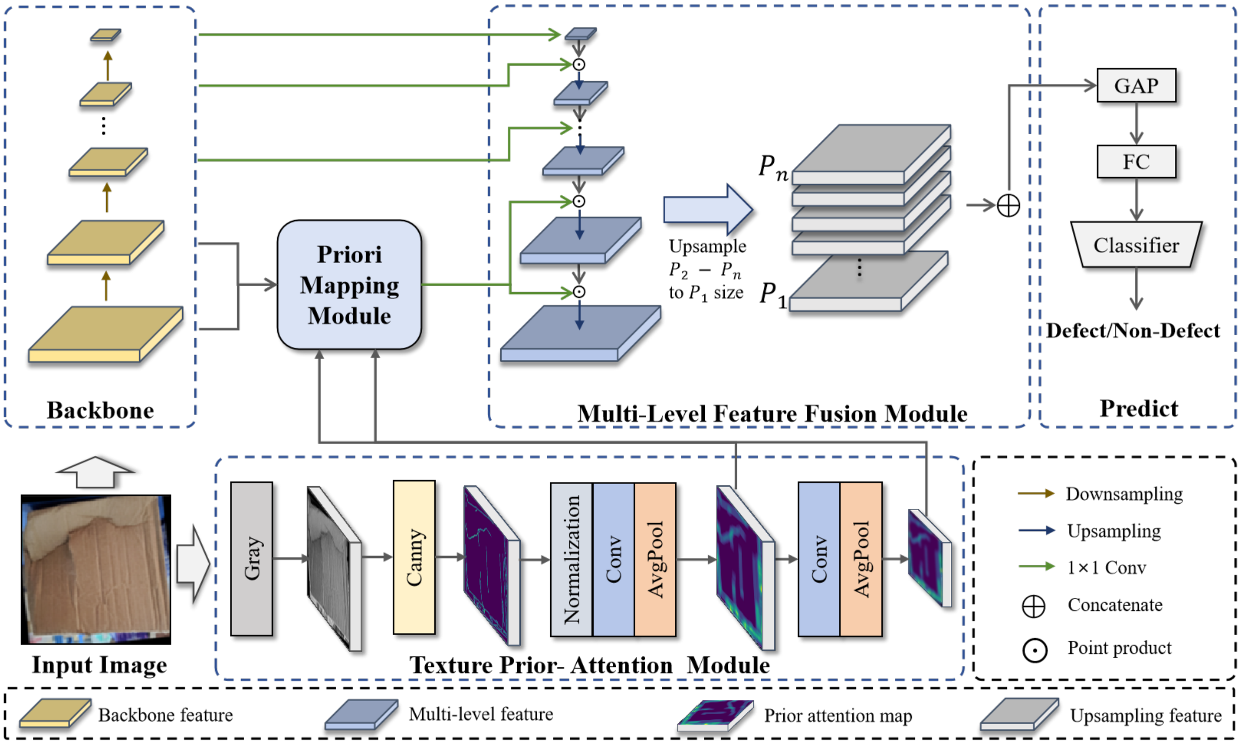


Fig. 2. Texture Prior-Aware Multi-Level feature fusion network.

a convolutional neural network (CNN) integrated with an attention mechanism to enhance training stability and detection accuracy in tactile methods for fabric structural defect detection [20]. However, the methods designed based on the specified material features mentioned above are not applicable to the complex defect scenarios in corrugated cardboard box defect detection [12], [21], [22]. Specifically, as illustrated in Fig. 1, the datasets for various defect detection tasks exhibit significant differences in features. Given the unique features of express packaging materials, we have devised an innovative model for surface defect detection.

B. Prior Attention

Prior attention enables the model to focus on important regions in the image, thereby improving the accuracy of object detection or image classification. Specifically, attention mechanisms allocate different weights to different parts of the input, allowing the neural network to concentrate on specific regions. SENet introduces a structure called the “Squeeze-and-Excitation” block, enabling the model to adaptively learn relationships between input feature channels [23]. DANet incorporates parallel global and local attention modules, focusing on global context and local details, respectively [24]. The role of prior knowledge in attention mechanisms is to introduce previous experience or assumptions to guide the neural network in focusing on specific information during the learning process. Cai et al. introduced image noise and edges as prior knowledge into the neural network, significantly enhancing the detection performance [25]. Wang et al. generate prior attention maps through a binary classifier to enhance lesion detection in COVID-19 CT screenings [26]. Zhang et al. assigns different weights to positions based on the prior that objects are near the image center and perceives object context information through different receptive fields [26]. However, existing prior attention methods are not applicable to the detection of defects in corrugated cardboard boxes, which focus more on regions rich in surface textures.

C. Multi-Level Feature Fusion

The task of multi-level feature fusion aims to effectively integrate feature information from different levels to enhance the performance of deep learning models when handling multi-level input data. HyperNet achieves effective multi-level feature fusion by aggregating hierarchical features and compressing them into a uniform space, enabling superior object detection performance across various levels [13]. Single shot multiBox detector achieves multi-level feature fusion by predicting category scores and box offsets for default bounding boxes using small convolutional filters [27]. Feature pyramid networks utilize a top-down architecture with lateral connections to facilitate effective multi-level object detection by integrating contextual information [28]. This method also finds extensive applications in other fields, such as remote sensing images [29], [30], classification of agricultural pests [31], and medical applications [32], [33], and so on. However, the above methods do not fully consider the texture information of low-level images, making it difficult to effectively integrate texture features on corrugated cardboard boxes at different levels and overall structures.

III. Texture Prior-Aware Multi-Level Feature Fusion Network

The overall architecture of the texture prior-aware multi-level feature fusion network is depicted in Fig. 2. Our network mainly consists of four parts: backbone, texture prior attention module, priori mapping module, and multi-level feature fusion module. We employ data augmentation techniques including mirroring, scaling, rotation, and translation to boost the diversity and complexity of the samples in light of the small number of samples in the dataset. This helps reduce the overfitting problem of the model. Enhanced images are created by randomly augmenting the original images, which are then sent into the backbone and texture prior attention module. Afterwards, we introduce each module of the network separately.

A. Backbone

ResNet-18 [16] provides strong feature learning capabilities for image features at various levels and abstraction levels. It is critical for detecting package defects, which typically manifest as local detail changes in the image, and ResNet-18 is capable of capturing these subtle features. Therefore, we designed the backbone based on ResNet-18. The ResNet-18 was constructed from residual blocks. ResNet-18 has N residual blocks, with each residual block's input set to x_i. The first block's input is an enhanced image, and the inputs of subsequent blocks are drawn from the previous block's output. The calculation for each residual block in ResNet-18 is as follows.

$$F^1_{RB} = ReLU(Conv(BN(Conv(x)))) \tag{1}$$

$$F^i_{RB} = ReLU(Conv(BN(Conv(F^{i-1}_{RB})))), i = \{2, \dots, n\} \tag{2}$$

where F^i_{RB} represents the output of the i-th residual block. $Conv$ stands for convolution, BN for batch normalization, and $ReLU$ for rectified linear unit.

B. Texture Prior Attention Module

Humans frequently rely on "textured" parts, such as zigzag edges and depressed creases, to determine whether corrugated boxes are distorted or leaking. Moreover, the value of each pixel in an RGB image is determined by the richness of the surrounding texture. We propose a canny-based prior attention method for texture recognition that extracts wrapped texture features as priori knowledge, allowing the model to pay more attention to essential texture areas. Experiments have shown that the prior attention map improves model performance significantly.

We first convert the image to grayscale before using the canny algorithm to extract the edges. The texture feature map is then min-max normalized to ensure that the value of each pixel is between 0 and 1, in order to obtain the prior knowledge map. The calculation process is as follows:

$$F_C = Canny(Gray(x), C_{lower}, C_{upper}) \tag{3}$$

$$T = \frac{F_C – min(E_C)}{max(F_C) – min(F_C)} \tag{4}$$

where, $Gray$ represents converting the input image x to a grayscale image, $Canny$ represents the Canny edge detection algorithm, and C_{lower} and C_{upper} indicate the lower and upper thresholds. T denotes the feature map after Max-Min normalization.

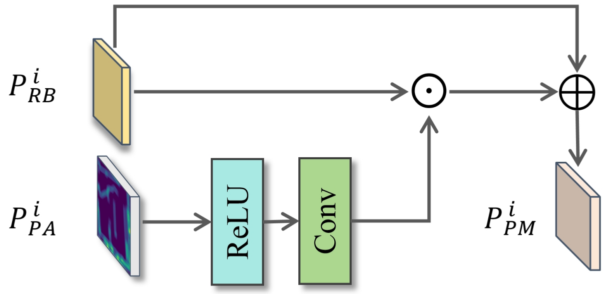


Fig. 3. The priori mapping module.

Included in the texture feature should be the surrounding texture-rich area as well as the texture itself. We extend the attention space even more by using downsampling and average pooling layers. Specifically, through the local perceptiveness of convolution and the information integration of average pooling, the expansion of texture edges can be achieved. This process allows the final Prior Attention Map to cover both the texture edges and the nearby texture information. The size of the output image after average pooling is the same as the size of the RGB branch feature map. Each feature downsampling module includes a 3×3 convolutional layer with 16 channels, followed by a 7×7 average pooling layer. The preceding method is as follows:

$$F^1_{PA} = AvgPool(Conv(T)) \tag{5}$$

$$F^2_{PA} = AvgPool(Conv(F^1_{PA})) \tag{6}$$

where F^i_{PA} represents the prior attention map at the i-th layer. $AvgPool$ is an acronym for average pooling.

C. Priori Mapping Module

The primary function of the Prior Attention Mapping module is to map the prior attention map to the enhanced feature map of the image obtained from the backbone. We consider fusing texture features and image features in the shallow layer of the network since downsampling the prior attention map leads to an erroneous attention range. The overview of this module is illustrated in Fig. 3.

This module gets the backbone feature F_{RB} of size $H \times W \times C$ from the encoder shallow layer and the texture prior attention module's prior attention map F_{PA} of size $H \times W \times 16$ as input and outputs the fusion feature F_{PM}. The process is as follows:

$$K = ReLU(Conv(F^i_{PA})), i = \{1, 2\} \tag{7}$$

$$F^i_{PM} = F^i_{RB} \odot K + F^i_{RB} \tag{8}$$

where, $\odot$ stands for dot-product. To prevent the above procedure from producing too small values and causing the gradient to vanish, we use the residual technique to let another F^i_{RB} skip the priori mapping module and add it to $F^i_{RB} \odot K$. This ensures that the performance of the network with the attention map will not be poorer than the original performance. Specifically, this module is applied to the output of block1 and block2 of the encoder.

D. Multi-Level Feature Fusion Module

In order to better incorporate high-level semantic information from images and prevent low-level semantic information, including texture features, from vanishing during the training process. We design the multi-level feature fusion module based on the feature pyramid network mechanism. Consider that there are n blocks in the multi-level feature fusion module. Defined the input consists of the priori mapping map F^1_{PM}, F^2_{PM} obtained in the priori mapping module and the backbone feature F^i_{RB} of various sizes obtained in the backbone. The output of each block as F^i_{MF}, where, $i \in \{1,..,n\}$. The module's ultimate output is the final fusion map P, which integrates feature maps from all levels. The final output of this module is the fusion of feature maps from all levels, denoted as P. Later, we will explain the specific details.

In order to preserve the rich texture information contained in low-level semantics, the lowest-level multi-level features need to be fused with the priori mapping map F^i_{PM} and the upper-level multi-level features F^{i+1}_{MF}. The process is as follows:

$$F^1_{MF} = Conv(F^1_{PM}) \odot F^2_{MF} \tag{9}$$

$$F^2_{MF} = Conv(F^2_{PM}) \odot F^3_{MF} \tag{10}$$

where $Conv$ stands for the convolution. $\odot$ stands for dot-product. F^1_{MF} and F^2_{MF} represent the priori mapping maps for the first and second layers, respectively. F^i_{MF} denotes the multi-level features for the i-th layer.

In multi-level features from the third layer and above, the model focuses more on the high-level semantic information of corrugated cardboard boxes. Therefore, the fusion of multi-level features from the third layer and above involves the backbone feature F^i_{RB} from the backbone and the upper-level multi-level features F^{i+1}_{MF}. The computation is as follows:

$$F^i_{MF} = Conv(F^i_{RB}) \odot F^{i+1}_{MF}, i = \{3, ..., n-1\} \tag{11}$$

$$F^n_{MF} = Conv(F^n_{RB}) \tag{12}$$

where F^i_{RB} represents the backbone feature for the i-th layer. For the multi-level feature F^n_{MF} in the nth layer, which doesn't have upper-level features, we only need to consider the nth layer's backbone feature F^n_{RB}.

In order to further fuse maps of different levels, we upsample each F^i_{MF} to the same size as F^1_{MF} using different factors, denoted as p_i. After that, we process the features with the following:

$$P = Concate\{F^1_{MF}, p^2, \ldots, P^n\} \tag{13}$$

where $Concate$ represents connecting features by channel dimension.

E. Predict and Loss Function

In addition to the aforementioned modules, it is essential to incorporate an additional classifier that takes the final fusion map as input to detect whether the corrugated cardboard box has defects. Specifically, the features that the multi-level feature fusion module outputs are average pooled and input to a fully connected network classifier for classification. The training goal is to minimize the cross-entropy loss function, aiming to make the predicted probability $\hat{y}$ closely match the true label y:

$$L = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)) \tag{14}$$

where N denotes the total number of samples in the test set. y_i represents the ground truth label of the i-th sample, taking binary values (0 or 1). $\hat{y}_i$ represents the predicted probability of the i-th sample.

IV. Experiment

In this section, we first introduce the data we collected, known as the cardboard-boxes-dataset. Then, we detail a series of experiments we conducted to test on cardboard-boxes-dataset. Additionally, we analyze the critical roles of several key modules designed by us in neural network learning through visualization.

A. Dataset

We provide a detailed overview of the data collection and feature labeling processes, as well as the specific details of dataset split.

1) Data Collection and Feature Labeling: In cardboard-boxes-dataset, we collected a total of 1210 images of packages. Among them, 761 images are from packages that have undergone express delivery and were actually delivered. The remaining images were obtained by purchasing new corrugated cardboard boxes of different sizes and manually simulating various types of defects that might occur to packages before capturing images.

We used LabelMe* to annotate detailed auxiliary information for 990 images, which can be used for tasks such as package localization and defect detection.

The annotation process involved two experts and was conducted in two rounds due to slight differences in their psychological expectations regarding whether the packages were defective. In the first round, each expert independently labeled each package image without any communication. Images that both experts found ambiguous or impossible to categorize were eliminated (225 images). In the second round, the experts continued to label the images without communication. The consistency of the labeling results was assessed using Cohen's Kappa:

$$k = \frac{p_0 - p_e}{1 - p_e} \tag{15}$$

where p_0 is the actual probability of agreement between the two experts, and p_e is the probability of agreement due to chance.

*https://github.com/wkentaro/labelme

TABLE I. COMPARISON EXPERIMENTS OF ATTENTION NETWORKS

Times	CE				Acc			
	SENet	DANet	AttNet	Our Method	SENet	DANet	AttNet	Our Method
1	0.5202	0.516	0.5342	0.4625	0.8365	0.8428	0.8365	0.8805
2	0.5193	0.4779	0.5353	0.4753	0.8616	0.8679	0.8176	0.8742
3	0.5214	0.4925	0.5289	0.5114	0.8491	0.8742	0.8239	0.8553
4	0.5017	0.5098	0.5109	0.4856	0.8742	0.8553	0.8428	0.8742
5	0.4979	0.4726	0.5241	0.4932	0.8428	0.8679	0.8302	0.8742
6	0.5353	0.5096	0.5107	0.4986	0.8365	0.8491	0.8491	0.8491
7	0.4771	0.4985	0.5234	0.4953	0.8553	0.8742	0.8239	0.8679
8	0.5008	0.5322	0.5607	0.4770	0.8491	0.8302	0.8239	0.8679
9	0.5002	0.4878	0.5227	0.5323	0.8679	0.8428	0.805	0.8176
10	0.5364	0.4879	0.5342	0.4641	0.8553	0.8616	0.8113	0.8868
Average	0.5110	0.4984	0.5285	**0.4895**	0.8528	0.8566	0.8264	**0.8647**
Min CE/Max Acc	0.4771	0.4726	0.5107	**0.4625**	0.8742	0.8742	0.8491	**0.8868**
variance	0.0186	0.0184	**0.0143**	0.0215	**0.0126**	0.0150	0.0136	0.0199

TABLE II. DATASET SPLIT

	Positive Samples	Negative Samples	Total
Training Set	191	287	478
Validation Set	80	80	160
Test Set	79	80	159
Total	350	447	797

TABLE III. PREDICTION EXPERIMENTAL RESULTS OF TPMN AND MN-TPMN ON THE TEST SET

Times	CE		Acc	
	TPMN	MN-TPMN	TPMN	MN-TPMN
1	0.4625	0.4746	0.8805	0.8994
2	0.4753	0.5361	0.8742	0.8113
3	0.5114	0.4742	0.8553	0.8742
4	0.4856	0.5126	0.8742	0.8239
5	0.4932	0.4924	0.8742	0.8553
6	0.4986	0.5043	0.8491	0.8742
7	0.4953	0.4776	0.8679	0.8805
8	0.4770	0.4979	0.8679	0.8679
9	0.5323	0.5148	0.8176	0.8428
10	0.4641	0.5646	0.8868	0.7925
Average	**0.4895**	0.5049	**0.8647**	0.8522
Min CE/Max Acc	**0.4625**	0.4742	0.8868	**0.8994**
variance	**0.0215**	0.0288	**0.0199**	0.0339

The final result is 0.6179, indicating a high level of consistency ($\geq$ 0.61 and $<$ 0.8) in the labeling results between the two experts. This implies a highly unified standard regarding whether the packages are defective. After removing inconsistent images labeled by both experts, there are a total of 350 images of non-defective packages and 447 images of defective packages.

2) Dataset Split: The dataset is randomly split into training, validation, and test sets with a ratio of 6:2:2, ensuring a balanced distribution of positive and negative samples in the validation and test sets to avoid data imbalance during validation and testing. Details are shown in Table II.

B. Hyperparameter Setting

TPMN is implemented by TensorFlow 2.8.The GPU used for training is the NVIDIA GeForce RTX 3090 24G. The input size of the backbone is 224×224×3, and the input size of the texture prior attention module is 224×224×1. The canny's upper threshold is 140 and its lower threshold is 80.

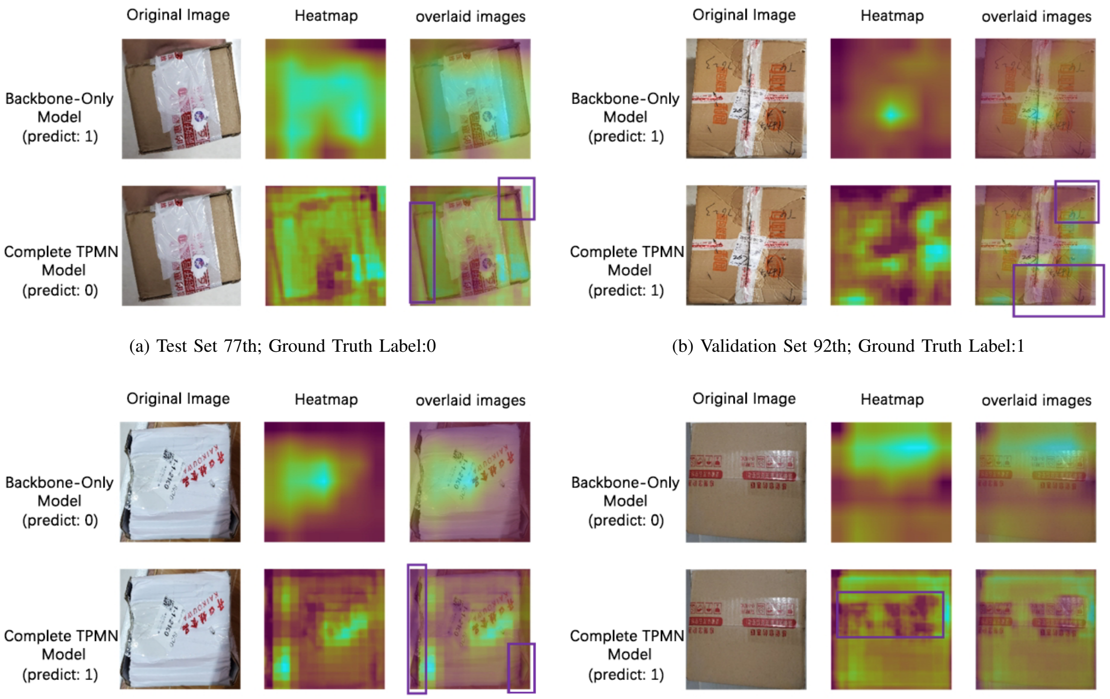
The chosen optimizer is Adam, with a learning rate of 0.001 and a decay of 0.002. The batch size is set to 128. Early stopping is implemented with a patience of 10, monitored by the cross entropy. The fully connected layers have 32 and 64 units, and the channels of multi-level feature fusion module are set to 32. Label smoothing is applied with a coefficient of 0.2.

C. Experimental Results

The model evaluation metrics include cross entropy (CE) and accuracy (Acc). Additionally, to better assess the model's performance, we will also separately consider metrics such as average cross entropy, average accuracy, minimum cross entropy, maximum accuracy, as well as the variance of cross entropy and accuracy. We additionally designed the Backbone of the TPMN based on MobileNet, known as MN-TPMN. The model was trained and tested a total of 10 times. All models were trained and tested in the cardboard-boxes dataset for a total of 10 times, and predicted whether the package was defective in the validation set.

The basic experimental prediction results, as shown in Table.III, demonstrate that the TPMN performs exceptionally well, exhibiting lower CE values and a higher average Acc. Compared to MN-TPMN, TPMN has a 1.5% lower average CE and a 1.2% higher average Acc. Each variance indicates that TPMN shows better stability.

We also compared our method with other attention mechanism networks: AttNet, SENet [16], and DANet [24]. The backbone network for these three models is ResNet-18, and the other training parameters are kept consistent with our training approach. AttNet is a spatial attention network that we re-implemented based on ResNet-18 [16]. The results, as shown in Table I, demonstrate that TPMN achieves optimal performance in terms of both CE and Acc compared to other


Original Image
Heatmap
overlaid images
Backbone-Only Model (predict: 1)
Complete TPMN Model (predict: 0)
Original Image
Heatmap
overlaid images
Backbone-Only Model (predict: 1)
Complete TPMN Model (predict: 1)
Original Image
Heatmap
overlaid images
Backbone-Only Model (predict: 0)
Complete TPMN Model (predict: 1)
Original Image
Heatmap
overlaid images
Backbone-Only Model (predict: 0)
Complete TPMN Model (predict: 1)

(a) Test Set 77th; Ground Truth Label:0

(b) Validation Set 92th; Ground Truth Label:1

(c) Validation Set 141th; Ground Truth Label:1

(d) Validation Set 141th; Ground Truth Label:0

Fig. 4. Visualization of the attention map of the convolutional layer. Each subfigure includes the original image in the first column, the heatmap of attention from the convolutional layer extracted by GradCAM in the second column, and the overlay of the first two images in the third column.

TABLE IV. Ablation Study

	Backbone	MFF	TPA	Average	Min CE Max Acc	variance
CE	✓			0.5220	0.4869	0.0226
	✓	✓		0.4929	0.4837	**0.0066**
	✓	✓	✓	**0.4895**	**0.4625**	0.0215
Acc	✓			0.8327	0.8553	0.0209
	✓	✓		0.8528	0.8679	**0.0122**
	✓	✓	✓	**0.8647**	**0.8868**	0.0199

attention mechanism networks. The higher variance of 1.2% is attributed to the complexity of texture patterns, leading to frequent changes in attention weights. In summary, TPMN exhibits substantial advantages in the logistics package defect detection task, proving the efficacy of our designed Texture Prior Attention Module.

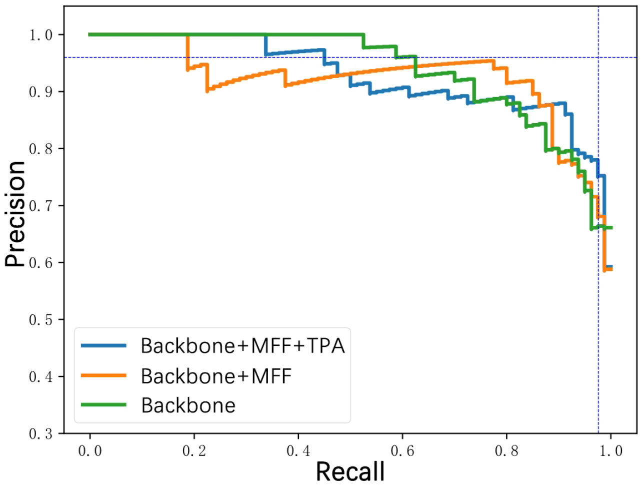


Fig. 5. PR curves from ablation experiments.

D. Ablation Study

To demonstrate the effectiveness of each module of TPMN, we conducted the following ablation studies: 1) The complete network, TPMN; 1) backbone whitout the texture prior attention module (TPA) from our proposed model; 2) backbone whitout the texture prior attention module(TPA) and the multi-level feature fusion module (MFF). As shown in Table.IV , compared to the backbone, we can observe that the utilization of MFF leds to an decrease in the average CE from 0.522 to 0.489, and a increase in the average ACC from 0.832 to 0.852. Considering the optimal values the model can achieve, the maximum accuracy increase by 1.26%. Furthermore, compared to the backbone, the combined use of TPA and MFF shows a significant decrease of 5% in the average CE, and decrease of 2.3% int the minimum CE. Meanwhile, Backbone-only model exhibits a pattern where its average ACC is 2.01% lower than backbone without TPA and 3.2% lower than the complete network. This indicates that, with the TPA and MFF, the model's average performance is much better than both backbone and backbone without TPA. Experiments prove the effectiveness of the two modules we designed.

The P-R curves for the three models on the validation set

TABLE V. Few-shot Learning Experiment

	Model	Size of Training Set					
		All	200	100	50	20	10
CE	Backbone	0.4869	0.5837	0.6043	0.6627	0.8467	0.8332
	Backbone+MFF	0.4837	0.5694	0.5522	0.6180	**0.7193**	0.7607
	Backbone+MFF+TPA	**0.4625**	**0.4896**	**0.5363**	**0.5872**	0.752	**0.6612**
Acc	Backbone	0.8553	0.7610	0.7673	0.6918	0.6352	0.5723
	Backbone+MFF	0.8679	0.8302	0.7925	0.7421	**0.6667**	0.5912
	Backbone+MFF+TPA	**0.8868**	**0.8616**	**0.8365**	**0.7484**	**0.6667**	**0.7044**

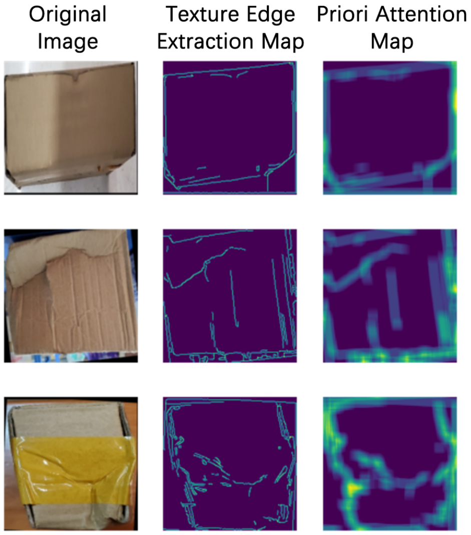


Fig. 6. Visualization of texture feature extraction.

are shown in Fig. 5, providing a preliminary insight into the workings of the two main modules. In situations where high precision is emphasized, the TPMN performs relatively worse compared to backbone with MFF, potentially misclassifying more intact packages as defective. Nevertheless, when Recall is greater than 0.85, TPMN outperforms the other control group, and backbone with MFF performs better than backbone-only model when Recall is greater than 0.7. This indicates that the TPMN is highly sensitive to defective packages. The texture prior attention module highlights the importance of texture, yielding better results for packages with rich textures. However, when the packages are non-defect, the model is less affected by effective textures, leading the attention towards patterns and text on the packages, which interferes with model training.

E. Visual Analysis

We first visualized the extraction of prior information from texture features. Then, we conducted a visual analysis of the impact of the prior attention map on the model training.

1) Visualization of Texture Extraction: We conducted an analysis of the effectiveness of the Texture Prior-Attention Module in extracting texture features. In Fig. 6, after Canny edge detection, the texture edges of the corrugated cardboard were successfully extracted, but the nearby texture information was not included. The final Prior Attention Map, obtained through convolution and average pooling, expands the attention range along the texture edges, thereby accommodating richer texture information. Through the local perceptiveness of convolution and the information integration of average pooling, the expansion of the attention range on the texture can be achieved.

2) Visual Analysis of Model Effectiveness: To provide additional evidence of the effectiveness of our approach, we conduct visual analysis on both the backbone-only model and the complete TPMN model. We analyze the model and classification results from the perspective of original images and convolutional layer attention. The attention map of the convolutional layer is obtained using the GradCAM [34] applied to the model's output and its last convolutional layer. Fig. 4a Fig. 4b and Fig. 4c demonstrate the advantages of the two main modules. TPMN can more accurately locate and focus on edge features, leading to accurate predictions. Without the two modules, backbone can only make predictions by broadly attending to various regions of the image, making it difficult to achieve the same performance. Fig. 4d, illustrates another extreme. When there are clear patterns or text on non-defect packages, the performance of the TPMN tends to decline. Due to the attention mechanism, the model's attention is forced to concentrate on information unrelated to the defect of package, resulting in prediction errors.

F. Few-Shot Learning Experiment

This section aims to investigate whether the model can maintain excellent performance with a reduced amount of data. Five sets of experiments were designed, each trained on different-sized training sets, and their final performance was measured. Despite variations in training set sizes, all datasets were processed using the data augmentation methods mentioned earlier.

The experimental results are shown in Table V. Regardless of the dataset size, TPMN has the highest Acc among all models, and CE also reaches the lowest in all five experiments. This indicates that the TPMN is able to maintain great performance even under conditions of limited data.

Attention mechanisms based models on often require larger datasets for training [35]. However, the TPMN excels on smaller datasets, because our designed prior attention and multi-level feature fusion methods effectively extract low-level texture features and Fusion multi-level features.

V. Conclusions and Future Work

In this study, we proposed a novel approach named the Texture Prior-Aware Multi-Level Feature Fusion Network to address the challenges in surface defect detection for corrugated cardboard boxes used in the logistics industry. Our method integrates a multi-level feature fusion technique that preserves and utilizes information from different semantic levels, overcoming the limitations of traditional Convolutional Neural Network (CNN)-based methods, which often suffer from the loss of local information and insufficient semantic details. The introduction of a prior attention mechanism enables the neural network to focus on extracting low-level texture features from the images in the early stages. The TPMN model, being model-agnostic, effectively extracts and fuses low-level texture features while comprehensively perceiving multiscale image information.

We conducted extensive experiments on our newly contributed Cardboard-Boxes-Dataset, which comprises 1210 images of packages. The results consistently demonstrated the superior performance of the TPMN model in precise defect classification and localization compared to traditional methods. The integration of ResNet-18, multi-scale feature fusion, and a prior attention mechanism proved effective in addressing the challenges unique to the logistics industry, where courier parcels, especially those made of corrugated cardboard, can exhibit varying defect sizes and structural complexities.

In the Future, there are several promising directions for further research and enhancement of TPMN. Firstly, expanding the dataset by incorporating diverse samples under varying environmental conditions would strengthen the model's robustness and generalization capabilities. Additionally, extending the application of the TPMN model to detect defects in different packaging materials commonly encountered in logistics, such as plastic or composite materials, could enhance its versatility. Exploring optimization strategies for real-time deployment, considering computational efficiency and resource constraints, is crucial for practical implementation in logistics settings. Integration with robotic systems for automated surface defect detection in logistics warehouses represents a potential avenue to improve efficiency and reduce manual intervention. In summary, the TPMN model lays a foundation for effective surface defect detection, and future research endeavors can capitalize on these insights to address evolving challenges in the dynamic logistics industry.

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An Ensemble Dynamic Model and Bio-Inspired Feature Selection Method-based Decision Support System for Predicting Multiple Organ Dysfunction Syndrome in the ICU

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Abstract—**Multiple Organ Dysfunction Syndrome (MODS) is one of the most common and severe conditions affecting patients admitted to intensive care units (ICUs). It is characterized by the simultaneous failure or dysfunction of at least two organ systems. Although no specific remedy for MODS has been identified to date, early diagnosis and adequate organ support can significantly improve patient outcomes. Identifying patients at risk of developing MODS in the ICU is challenging. Currently, several methods are used for this purpose, including scoring systems like SOFA and MOD Score, as well as machine learning-based approaches. However, these methods often have limitations. Some require invasive features, making them complex to use in a smart healthcare system. Others suffer from a lack of performance due to various problems, which can potentially lead to unreliable predictions. Feature selection can improve ML models' performance. Recently, bio-inspired feature selection techniques have shown promise in improving the performance of machine learning methods in many domains, but their effectiveness in MODS prediction has not yet been evaluated. Additionally, research on early MODS prediction, particularly utilizing time-series data and dynamic ensemble methods, remains limited. To fill this gap, the present research used state-of-the-art machine learning algorithms, namely dynamic ensemble techniques, to predict patients at risk of developing MODS in the ICU. Dynamic ensembles are new methods that select an ensemble of the best-performing models for every new test case. We compared the performance of these models with full features and with feature selection. Three nature-inspired meta-heuristic optimization models, namely the binary bat algorithm (BBA), grey wolf optimization (GWO), and genetic algorithm (GA), were evaluated to select the optimal feature subset. The models were built using non-invasive patient features and time-series data from the first 12 hours of ICU admission. The results showed that feature selection significantly improved the performance of dynamic ensemble models. Notably, the METADES model, employing grey wolf optimization for feature selection, demonstrated the best performance in terms of accuracy(96.5%), F1 score (96.4%), precision (97.2%), recall (95.7%), and area under the ROC curve (AUC) (98.4%). These findings highlight the potential and effectiveness of our approach for early MODS prediction in ICUs.**

Keywords*—*Ensemble dynamic model; MODS prediction; decision support system; Bio-Inspired feature selection

I. Introduction

Multiple Organ Dysfunction Syndrome (MODS) is widely recognized as a primary cause of death in critically ill patients, affecting 11% to 40% of adults admitted to intensive care units (ICUs) [1]. Accordingly, the high mortality rate of this syndrome, ranging from 44% to 76%, underlines its seriousness. MODS typically arises in response to severe illness or injury, often as a result of conditions like sepsis, severe trauma, major surgery, or prolonged shock. It involves the simultaneous dysfunction or failure of at least two organ systems, such as the heart, lungs, liver, and kidneys, etc. While the dysfunction is typically acute and severe, there is potential for reversibility, especially with prompt identification and treatment of underlying causes or triggers [2].

Despite extensive research, effective treatments for MODS remain elusive. Current interventions have not adequately controlled the excessive immune response or facilitated organ recovery. This has led to invasive organ support as the primary treatment approach in ICUs [1]. Additionally, a survey by the American Hospital Association (AHA) revealed that there are over 6,300 intensive care units in 3,200 acute care hospitals in the United States, providing a total of 94,000 ICU beds [3]. Consequently, the shortage of medical staff in ICUs exacerbates work pressures, affecting patient care quality and potentially leading to oversight of crucial changes in patient conditions [4]. Therefore, rapid diagnosis becomes essential for optimal resource allocation to the neediest patients. It's important to note that the implementation of early-phase management strategies, including a resuscitation approach focused on damage control and scoring systems, has contributed to an increased survival rate among injured patients upon admission to intensive care. Hence, fundamental aspects of MODS treatment involve early identification and support of organ functions. Several scoring systems have been developed to assess the severity of Multiple Organ Dysfunction Syndrome (MODS) and predict outcomes using clinical parameters. Among these, the SOFA score (Sequential Organ Failure Assessment) [5] is commonly utilized. The SOFA score is designed to monitor and predict the progression of organ failure by assessing the function of six organ systems: cardiovascular, liver, respiratory, coagulation, renal, and neurological [6]. Furthermore, each organ system is assigned a score ranging from 0 to 4, as shown in the Table I. A higher score reflects more severe failure. Organ failure is typically identified by a SOFA score exceeding 2 in one of the six assessed organ systems [7]. The total SOFA score is the sum of these individual scores, ranging from 0 to 24. However, the SOFA score is a complex tool that necessitates meticulous patient evaluation and the continuous collection of numerous parameters. Consequently, it may exhibit variability in predicting the outcome of MODS.

TABLE I. SOFA Score Parameters

Organ Systems	SOFA	Score
Respiratory	PaO2/FiO2 and ventilation	0 to 4
Coagulation	Platelet number	0 to 4
Hepatic	Bilirubin	0 to 4
Cardiovascular	Blood pressure and vasopressor use	0 to 4
Central nervous system	Glasgow Coma Scale	0 to 4
Renal	Creatinine urine output	0 to 4
Aggregate	Calculated daily	0 to 24

In recent years, there has been a gradual increase in research on intelligent intensive care units, with a focus on monitoring and risk prediction. By leveraging modern scientific and technological advancements such as 5G communication technologies, the Internet of Things, and big data analysis, coupled with machine learning techniques[4], these innovations hold promise in predicting the likelihood of an individual developing MODS in the ICU.

Many researchers have employed ensemble classifiers for clinical classification problems, with promising results [8] [9] [10][11]. Additionally, they have also explored Dynamic Ensemble Selection (DES) models [12][13] [14] that select an ensemble of classifiers dynamically for each test data item. This allows DES to identify patterns in complex domains like biomedicine, credit scoring, and handwriting recognition instead of relying on a single classifier for the entire dataset. While existing research on predicting Multi-Organ Dysfunction Syndrome (MODS) in ICU patients suggests room for improvement, we investigated DES techniques for this purpose. Our study compares them with diverse feature selection methods utilizing nature-based algorithms. Feature selection helps alleviate the “curse of dimensionality,” facilitating faster, simpler, and potentially more performant machine learning models. Analyzing relevant studies [15], [16], [17], [18], [19], we identified the Binary Bat Algorithm (BBA), Genetic Algorithm (GA), and Grey Wolf Optimization (GWO) as effective and prevalent feature selection algorithms. Our study employed these bio-inspired feature selection methods.

Following feature selection, we employed seven state-of-the-art DES models (META-DES, DESP, KNORA-U, DESKNN, KNORA-E, MCB, and KNOP) for classification. We comprehensively evaluated their performance using metrics like F1-measure, recall, sensitivity, precision, accuracy, and ROC curve analysis to select the optimal classifier. Additionally, Area Under the Receiver Operating Characteristic (AUROC) curve analysis assessed the impact of feature selection.

Our main objective is to develop a decision support system capable of accurately classifying and predicting patients at risk of having MODS in the ICU using only non-invasive features and time-series data from the first 12 hours after ICU admission. This system has the potential for integration into a smart healthcare monitoring system for intensive care units[8], as illustrated in Fig. 1.

The remainder of the document is structured as follows: Section II provides an overview of the current state of research in MODS, followed by Section III, which outlines the proposed methodology. Section IV presents the experimental results and subsequent discussion. Section V addresses the limitations of this study and suggests avenues for future research, while Section VI serves as the conclusion.

II. Related Works

To date, extensive research efforts have been dedicated to investigating the diagnosis of Multiple Organ Dysfunction Syndrome (MODS).Various medical and artificial intelligence-based methods have been employed, yielding significant results. This section undertakes a thorough examination of the literature concerning MODS diagnosis and related triggers, such as sepsis:

Bowen et al. [20] proposed an approach based on machine learning for predicting multi organ dysfunction syndrome (MODS) recovery in pediatric patients with sepsis. The authors highlight the lack of effective predictive models for early recovery from MODS in this patient group. The study introduces a novel methodology that anticipates the transition from MODS to milder states, utilizing datasets from Swiss and U.S. pediatric sepsis cohorts. The model demonstrated promising performance, achieving approximately 79.1% AUROC and 73.6% AUPRC during internal validation and 76.4% AUROC and 72.4% AUPRC during external validation. The suggested approach exhibits the potential for integration into electronic health record systems, thereby aiding in patient evaluation and prioritization within pediatric sepsis care. Furthermore, the researchers employ SHAP values to elucidate pivotal recovery factors as identified by the model. The study also explores associations between predicted outcomes and factors such as pathogens, infection sites, and age groups, contributing to an enhanced interpretation of the model’s predictions.

Guanjun et al. [21] proposed a study to develop models to predict multiple organ dysfunction syndrome (MODS) among trauma patients utilizing noninvasive predictors alone. Traditional methods of predicting MODS are invasive and difficult to implement in a pre-hospital environment. The study uses records from 2319 patients and employs seven machine learning methods to create real-time MODS prediction models. A comparison was made between the models and the four conventional scoring systems. The best-performing model is based on LightGBM (LGBM) and Adaboost, achieving a high AUC of 0.959 when using all parameters. Even when reducing the parameters to non-invasive ones only, the LGBM model still outperformed traditional scoring systems, with an AUC of 0.940. The study concludes that the accurate, real-time prediction approach using non-invasive features is superior to conventional scoring systems, which could facilitate early diagnosis and improve patient survival rates in the pre-hospital setting.

Chang et al. [22] proposed an advanced approach to the challenge of predicting and preventing multiple organ dysfunction syndrome (MODS), The study used machine learning

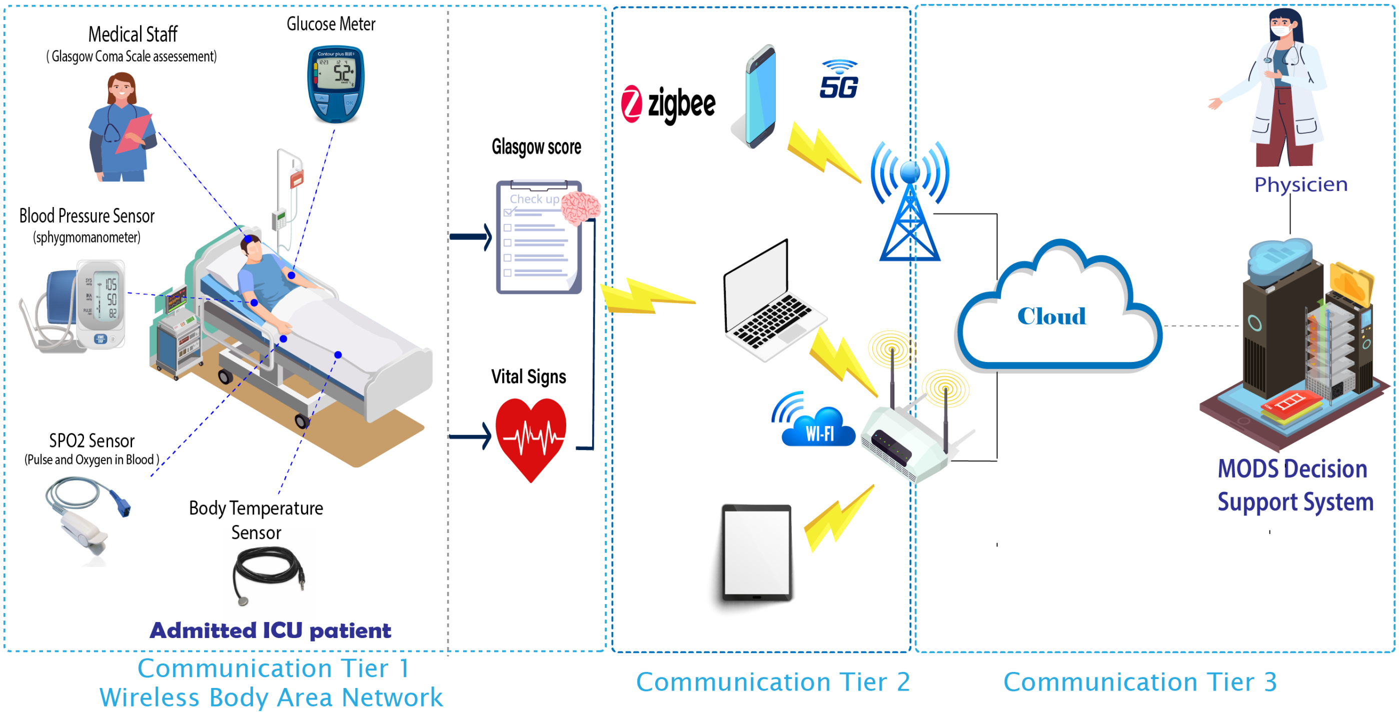


Fig. 1. General architecture of the predictive system for MODS in ICU.

algorithms to create early warning models for MODS risk assessment. The researchers developed a customizable model called SuperLearner by integrating several machine learning approaches, which resulted in high robustness in detection and favorable assessment measures such as sensitivity and accuracy. In addition, the deep neural network (DWNN) model showed excellent performance, with a notable AUC of 0.960 on the MIMIC-IV test set. This result highlighted the exceptional predictive power of the DWNN model in the context of MODS prediction. The research introduced additive Kernel-SHAP and various DiCE (counterfactual explanations) to interpret the results of the predictions and recommend interventions, enabling the prediction of MODS risk 12 hours in advance. The study utilized clinical features, scoring characteristics, and database data for model training, showcasing the potential application value of their approach for early MODS prediction and intervention. The integration of Q-learning for model selection and the combination of SuperLearner and SubSuperLearner structures were innovative contributions. The researchers also introduced a utility score for comprehensive performance assessment and incorporated DiCE to facilitate automatic intervention recommendations for improved practicality.

Tunc et al. [23] introduced a solution for monitoring sepsis-related symptoms and the condition of organ systems without the need for lab tests. Their work proposed the Deep SOFA-Sepsis Prediction Algorithm (DSPA), which combines features from Convolutional Neural Networks (CNNs) with the Random Forest (RF) algorithm to predict Sequential Organ Failure Assessment (SOFA) scores of patients diagnosed with sepsis using only seven vital signs collected in the Intensive Care Unit (ICU). They evaluated their model using the MIMIC III dataset and achieved a mean absolute error (MAE) of 0.65, a correlation coefficient (CC) of 0.86, and a root-mean-square error (RMSE) of 1.23 in predicting SOFA scores at the onset of sepsis. Their model demonstrated superior performance compared to traditional machine learning and deep learning models in regression analysis. Furthermore, they showcased strong classification performance, achieving an area under the curve (AUC) of 0.982 for predicting early sepsis, surpassing previous studies. The proposed framework offers a non-invasive and timely approach for predicting sepsis and monitoring organ states.

Alexis et al. [24] conducted a study on multiple dysfunction syndrome in children after congenital heart surgery involving cardiopulmonary bypass (CPB). The study involved 306 surgical patients under the age of 18 and collected biomarkers and clinical information. The model, called PERSEVERE-CPB, incorporated the level of interleukin 8 (IL-8) 12 hours after bypass surgery, the change in serum chemokine ligand 3 (CCL3) between 4 and 12 hours, and the infant's age category. PERSEVERE-CPB was able to efficiently stratify patients into categories of low, intermediate, and high risk for the development of persistent MODS, demonstrating the potential for targeted interventions and improved outcomes through the identification of high-risk patients. The discriminative performance of the model was comparable to reference tools such as the STAT model and the PRISM III score, with an AUROC of 0.86 (95% CI 0.81; 0.91) for discrimination between patients with and without persistent MODS. After 10-fold cross-validation, the PERSEVERE-CPB model maintained good performance, with a corrected AUROC of 0.75 (95% CI 0.68-0.84).

This concise overview underscores the significant interest within the scientific community regarding the diagnosis and prediction of Multiple Organ Dysfunction Syndromes (MODS). Despite the limited number of studies utilizing machine learning models for MODS prediction and the scarcity of research involving non-invasive features, resulting in the complexity of implementing these models into an intelligent decision support system for early MODS prediction, it is clear that machine learning tools have yet to achieve widespread application in MODS diagnostic systems. This holds especially true in developing countries, where the mortality rate due to MODS remains alarmingly high, leaving considerable room for improvement. In this study, we introduce a novel approach based on a dynamic ensemble model and an advanced feature selection method for selecting the optimal feature set. Setting it apart from other methods, this approach is straightforward to implement, utilizes non-invasive features to forecast the risk of MODS occurrence in the ICU, and has exhibited outstanding performance in the detection and prediction of Multiple Organ Dysfunction Syndrome (MODS).

III. Proposed Methodology

In this study, our goal is to develop a Decision Support System based on a predictive model for predicting which patients are at risk of developing MODS in the ICU. To achieve this, we compared seven state-of-the-art Dynamic Ensemble Selection models (DES) that assess the skill of individual classifiers from a classifier pool. The most skilled classifier, or a set containing the most skilled classifiers, is then used to predict the correct label for a given test sample. We formulated a classification problem aimed at predicting the risk of a patient developing MODS based on extracted data gathered in the initial 12 hours following their admission to the intensive care unit.

The evaluation of the base classifiers was carried out through the cross-validation technique, and the DES models were assessed using a validation test set to estimate the ability of our model to generalize outside its trained dataset. Throughout our research, we explored various models and architectures, testing different feature sets by applying three nature-based optimization techniques.

The proposed methodology is outlined and visually represented in Fig. 2.

A. Study Design and Datasource

In this study, we employed MIMIC-III, a medical database containing anonymized records from more than 46,520 patients admitted to the intensive care units at Beth Israel Deaconess Medical Center in Boston, Massachusetts. The data spans from 2001 to 2012. The database has received ethical approval for use and is managed by the Massachusetts Institute of Technology's Computational Physiology Laboratory (MIT) under the PhysioNet-accredited Health Data 1.5.0 license. This extensive database comprises 26 tables containing a diverse range of data, such as demographic information, vital sign measurements, laboratory test results, medical procedures, medication records, caregiver notes, imaging reports, and mortality data upon discharge. These data are interconnected using key identifiers such as subject-ID, hadm-ID, and ICUSTAY-ID. In order to ensure patient confidentiality, a rigorous de-identification process was applied, aligning with the Health Insurance Portability and Accountability Act (HIPAA) standards in the United States. This process involved the removal of personally identifiable information, such as patient names, phone numbers, and specific dates. Additionally, a date-shifting method was employed to preserve temporal intervals in the data. We obtained approval to extract data from this database under (Record ID: 53063368).

B. Data Pre-Processing

These steps are designed to improve the overall quality of the selected dataset. The MIMIC III dataset contains a number of issues, such as outliers, missing values, etc. This can be the consequence of a sensor or data transfer failure, an error in data storage, etc. Building a model with such poor, incomplete data is regarded as the major factor behind underperforming models. The initial process of data preprocessing involves converting raw data to a convenient and useful format. This stage involves three distinct steps: cleaning the data, data transformation, and data reduction. Data cleaning focuses on resolving problems associated with missing data and anomalies. The data transformation phase aims to reshape the data so that it is more adaptable for data mining. Commonly used transformation techniques include attribute selection, normalization, etc. Finally, data reduction avoids the complications associated with processing large datasets. The next subsections deal with the measures taken to deal with these data problems.

1) Data extraction: Data were extracted from the MIMIC-III dataset (v1.4). Apache Spark software was used to extract baseline features (subject ID, ID of ICU stay, age, gender), vital signs, and non-invasive features as shown in Table II from patients meeting the criteria using SQL (Structured Query Language) as shown in the cohort selection Fig. 3, and to extract pertinent features to compute the SOFA scoring system.

Our decision to employ Apache Spark for data extraction from MIMIC-III was driven by its remarkable capability to efficiently handle large volumes of distributed healthcare data. Spark excels in distributed processing and provides a unified suite of tools, rendering it highly suitable for extracting and processing complex medical data at scale. Its fault tolerance and capacity to distribute workloads across a cluster of machines ensure the reliability and performance necessary for analyzing clinical data from MIMIC-III.

In addition to its data extraction capabilities, Apache Spark also offers a versatile environment for further data analysis, enabling researchers and healthcare professionals to gain valuable insights from this extensive medical dataset. The combination of MIMIC-III and Apache Spark has proven to be a powerful solution for in-depth healthcare analytics and research.

2) Missing data handling: A thorough understanding of data is of crucial importance when analyzing data in the healthcare context. The challenges inherent in this field call for proper management of missing data. Although the simplistic method of removing missing values is commonly used, it has the notable disadvantage of leading to a loss of significant information, thus reducing the number of data instances available for model training. In response to this problem, various strategies have been proposed for filling in missing values using alternative records, such as forward filling and

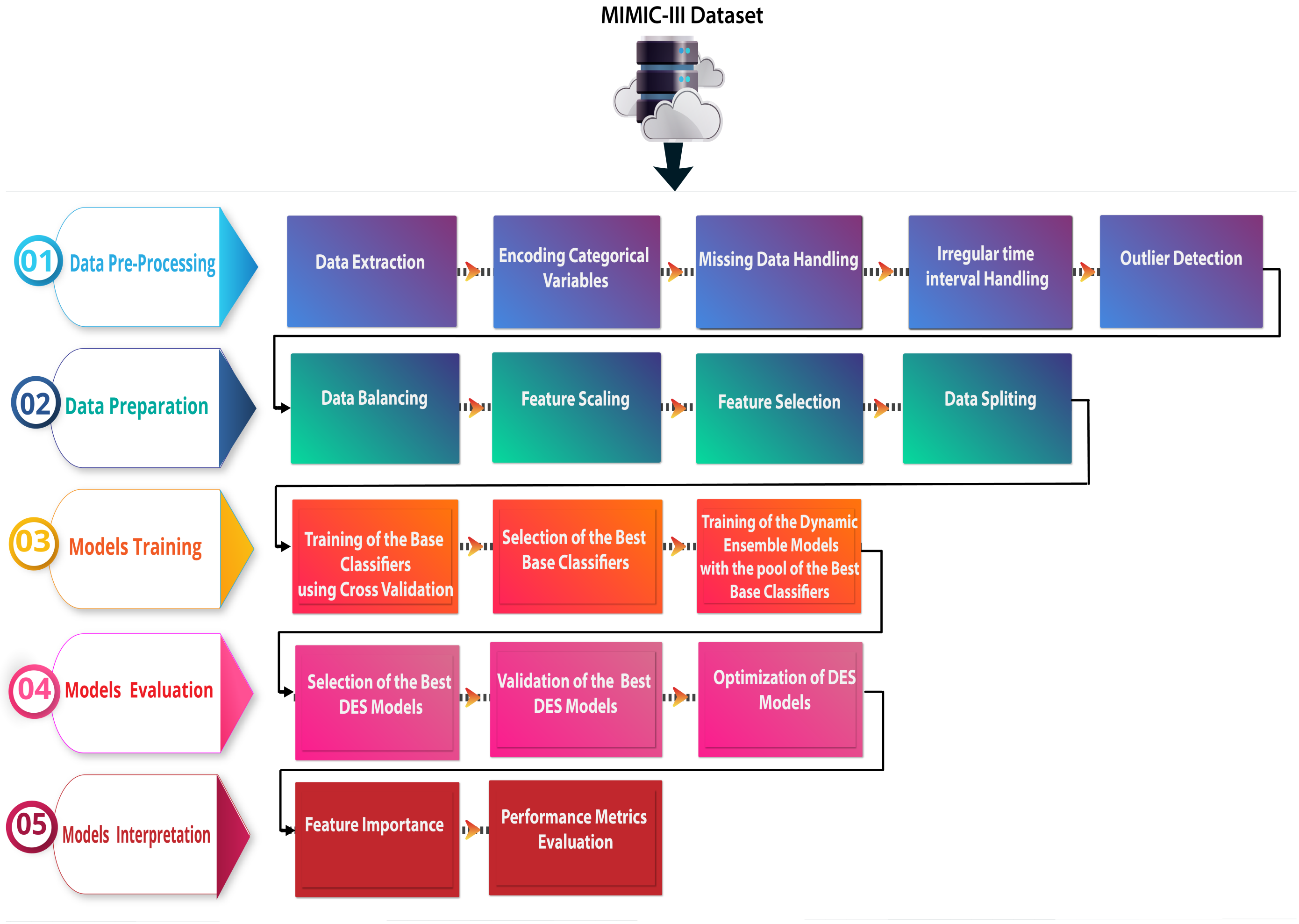

MIMIC-III Dataset
01 Data Pre-Processing
Data Extraction
Encoding Categorical Variables
Missing Data Handling
Irregular time interval Handling
Outlier Detection
02 Data Preparation
Data Balancing
Feature Scaling
Feature Selection
Data Spliting
03 Models Training
Training of the Base Classifiers using Cross Validation
Selection of the Best Base Classifiers
Training of the Dynamic Ensemble Models with the pool of the Best Base Classifiers
04 Models Evaluation
Selection of the Best DES Models
Validation of the Best DES Models
Optimization of DES Models
05 Models Interpretation
Feature Importance
Performance Metrics Evaluation

Fig. 2. The proposed approach.

the use of K-Nearest Neighbors. During the MIMIC III data pre-processing phase, a substantial proportion of crucial data (between 40 and 55%) is unfortunately lost. However, given its importance to the forecasting process, deleting this data was not an option. Faced with this challenge, we decided to select cases with two or more values in each measure, and then apply the forward filling method to impute the remaining missing values.

3) Outliers detection: In our study, special emphasis was placed on handling outliers within the medical dataset. The detection of outliers was performed using the interquartile range method to avoid the indiscriminate removal of records. Outliers were addressed in two steps: first, they were replaced with null values, considered missing, and then imputed using the forward-filling method.

4) Irregular time interval: In the MIMIC III dataset, the recording of vital signs occurred at irregular intervals, varying from measurements taken every few minutes to every few seconds. This irregularity in time intervals presented a challenge for machine learning techniques that typically operate with uniformly sampled data. To overcome this challenge, we aggregated patient vital sign observations, consolidating them into a single record every hour. This aggregation involved incorporating key statistical measures, including the standard deviation, mean, minimum value, maximum value, and count of all measurements within each hourly interval. As a result, each record now contains consistent values. In addressing further irregularities within the temporal intervals of time-series data, particularly with regard to balancing measurements for patients diagnosed with MODS in the dataset, we implemented a targeted approach. The initial step involved organizing the data by MODS patient ID and timestamp. Subsequently, each patient underwent individual processing to tackle irregular measurements by either eliminating excess or filling gaps with randomly generated dates. The handling of null values was achieved through the forward and backward filling methods, strategically replacing missing values based on predefined criteria. These meticulous steps ensure the consistency of measurements across temporal datasets, ultimately enhancing the quality and reliability of future analyses.

C. Data Preparation

1) Data balancing: The imbalance of classes is one of the most well-known and crucial issues that can influence the performance of machine learning algorithms. This issue occurs when classes are unequally represented. In unbalanced data, majority classes dominate minority classes. Consequently,

TABLE II. FEATURES USED IN THIS STUDY

Feature	Definition
Age	Admission age of the patient
Gender	Gender of the patient
Height	The measurement of a patient's vertical size. Used for assessing body proportions.
Weight	The measurement of a patient's mass. Used for various health assessments, including medication dosages.
Diastolic blood pressure	The pressure in the arteries when the heart is at rest. It is an essential indicator of cardiovascular health.
Systolic blood pressure	The pressure in the arteries when the heart contracts. Important for assessing cardiovascular health and blood flow.
Fraction inspired oxygen	The proportion of oxygen in the air or a gas mixture that is being inhaled. Important for assessing respiratory function and oxygen delivery.
Glucose	The level of glucose in the blood. A critical indicator of glycemic control and metabolic health.
Heart Rate	The number of heartbeats per minute. Crucial for assessing cardiac function and rhythm.
Oxygen saturation	The percentage of hemoglobin in the blood that is saturated with oxygen. It is important for evaluating respiratory function and oxygenation.
Respiratory rate	The number of breaths taken per minute. Essential for monitoring respiratory health and efficiency.
Temperature	The measurement of a patient's body heat. Crucial for monitoring body temperature and detecting fever or hypothermia.
pH	The measure of the acidity or alkalinity of the blood. Essential for evaluating acid-base balance and overall metabolic health.
Mean blood pressure	The average pressure refers to the average pressure in the arteries throughout one cardiac cycle. It serves as a crucial indicator of overall blood pressure.
Glasgow Coma Scale Eye Opening	used to evaluate a patient's level of consciousness by assessing their eye response.
Glasgow Coma Scale Motor Response	used to evaluate a patient's level of consciousness based on their motor response.
Glasgow Coma Scale Verbal Response	used to evaluate a patient's level of consciousness by assessing their verbal response.

since there are not enough instances of the minority class, an imbalanced classification has the disadvantage that a model cannot effectively learn the decision boundary, and machine learning approaches have a higher probability of classifying each new observation in the majority class. Consequently, the issue of unbalanced data can lead to the misclassification of minority classes. However, there is a significant need for an effective method that could address the class imbalance problem. In this study, the minority class has 172 samples, while the majority class has 940 samples, resulting in a ratio of 5.4:1, as depicted in Fig. 4. Thus, we employed an unsupervised technique, namely the Synthetic Minority Oversampling Technique (SMOTE)[25], to address the class imbalance issue in the datasets as depicted in Fig. 5.

2) *Feature scaling:* Feature scaling is a preprocessing technique used in statistics and machine learning to normalize the values of different features in a dataset. Often, datasets contain features that vary widely in terms of size, units, and range. The goal is to adjust the scales of features so that they are comparable, and no single feature dominates others due to its units or magnitude. The range of intensive care unit data points considered in this study is very diverse, and therefore it is necessary to perform feature scaling to minimize any effects on model performance. In our study, we have chosen Z-score scaling as our standardization method. This decision stems from the need to make our features robust to outliers, a crucial aspect in the context of our data. Unlike other methods, such as normalization, Z-score scaling minimizes the impact of extreme observations, ensuring a more balanced scaling of features. Moreover, this approach facilitates the interpretation of results, especially in the context of linear models, by providing directly comparable coefficients. By prioritizing standardization, our goal is to optimize the stability and convergence of machine learning models, thereby contributing to more reliable analyses and robust results within our study.

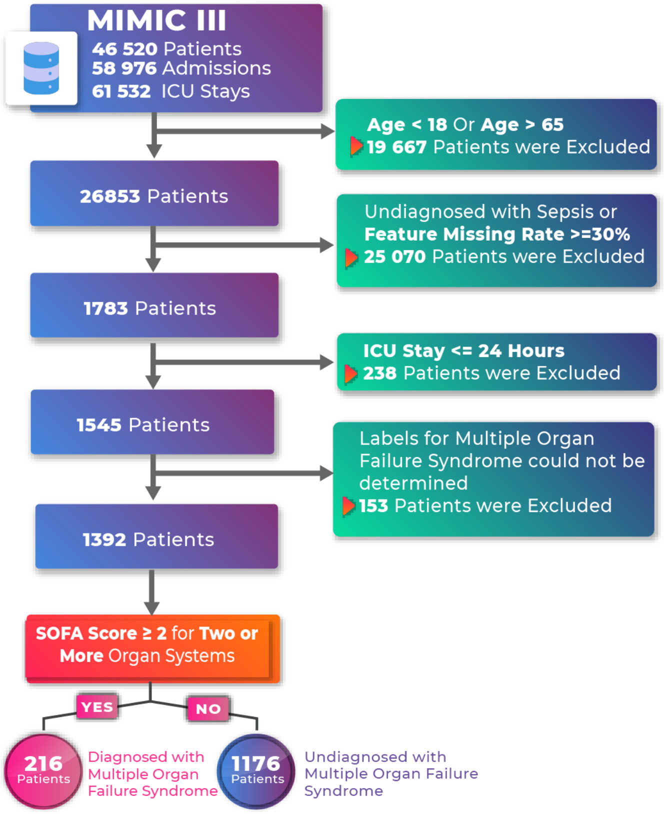

MIMIC III
46 520 Patients
58 976 Admissions
61 532 ICU Stays
Age < 18 Or Age > 65
19 667 Patients were Excluded
26853 Patients
Undiagnosed with Sepsis or
Feature Missing Rate >=30%
25 070 Patients were Excluded
1783 Patients
ICU Stay <= 24 Hours
238 Patients were Excluded
1545 Patients
Labels for Multiple Organ Failure Syndrome could not be determined
153 Patients were Excluded
1392 Patients
SOFA Score ≥ 2 for Two or More Organ Systems
YES
NO
216 Patients
Diagnosed with Multiple Organ Failure Syndrome
1176 Patients
Undiagnosed with Multiple Organ Failure Syndrome

Fig. 3. Cohort selection diagram from MIMIC dataset.

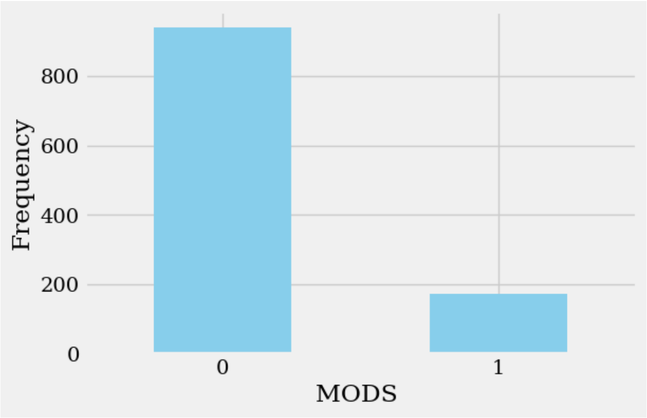


Fig. 4. Distribution of classes before applying the Smote technique.

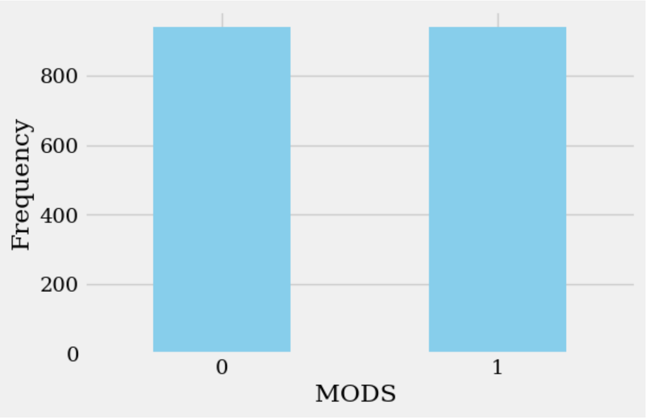


Fig. 5. Distribution of classes after applying the Smote technique.

3) Feature selection: Feature selection is an important component of feature engineering and plays a key role in improving the capability of machine learning algorithms [26]. The primary contribution of the proposed approach lies in its capability to carefully select a subset of features of interest from the set of extracted features, resulting in significantly improved prediction results. This diagnostic model employs an optimal feature selection approach. The primary objective is to emphasize relevant features while reducing the number of features to address redundancy issues. Overall, this methodology aims to minimize the feature set during the construction of the predictive model, leading to a reduction in computational costs and an enhancement in overall model performance. Recent studies highlight the effectiveness of Nature-Inspired optimization feature selection approaches, contributing to a notable increase in model performance and efficiency. The feature selection algorithms employed in this study involve:

a) Grey Wolf Optimization (GWO): The Grey Wolf Optimizer (GWO) [27] is a nature-inspired optimization algorithm. This algorithm simulates the cooperative and hierarchical hunting strategy of wolves, and its key steps are as follows:

Surround the Prey (Initialization): The algorithm begins by randomly placing a population of wolves in the search space, each representing a potential solution.

Hunting Behavior (Fitness Evaluation): Each wolf's fitness is evaluated using a fitness function, measuring its alignment with optimization goals and reflecting its hunting success in finding the optimal solution.

Hierarchy: Alpha, Beta, and Delta (Leadership Selection): Wolves are sorted based on their fitness levels. The top three wolves are identified as alpha, beta, and delta, establishing a leadership hierarchy within the pack.

Update Positions (Pack Movement): The positions of wolves are adjusted using a formula inspired by the social behavior observed in wolf packs. Alpha, beta, and delta play pivotal roles in directing the movement of other wolves toward potentially optimal solutions.

Exploration and Exploitation (Hunting Strategy): The hierarchy ensures a balance between exploration and exploitation. Alpha, beta, and delta lead the exploration, while other wolves follow, exploring around their positions to discover potential solutions.

Surrounding the Prey (Optimization): The algorithm iterates through these stages, progressively refining the positions of wolves. This mimics the way a wolf pack surrounds prey during a hunt, improving the chances of finding the optimal solution.

Criteria for Completion (End of Hunt): The algorithm continues these stages for a defined number of iterations or until a predefined termination criterion is met. The final positions of the wolves represent the optimized solutions.

b) Binary Bat Algorithm (BBA): The Binary Bat Algorithm (BBA), detailed in [28], is an optimization algorithm inspired by the echolocation behavior of bats. It is specifically engineered for tackling binary or combinatorial optimization problems. It simulates bats' use of ultrasonic pulses for navigation and prey location, incorporating features like frequency and intensity modulation, as well as global and local search mechanisms. BBA has demonstrated versatility and effectiveness in addressing various optimization problems since its inception.

The Binary Bat Algorithm (BBA) comprises the following key steps:

Sonar Scanning (Initialization): Initialize a population of binary bats randomly within the search space, representing potential feature subsets.

Fitness Echo (Objective Function Evaluation): Evaluate the fitness of each bat solution using a task-specific objective function for feature selection.

Leadership Hierarchy (Alpha, Beta, and Delta Bats): Establish a leadership hierarchy by designating the top-performing bats as alpha, beta, and delta.

Echo-Driven Movement (Flight Adjustment): Adjust the positions of bats, guided by alpha, beta, and delta, influencing the exploration of potential optimal feature subsets.

Adaptive Echolocation (Exploration and Exploitation): Maintain a balanced exploration and exploitation strategy, with alpha, beta, and delta leading exploration and other bats following suit.

Echo-locative Refinement (Optimization Iterations): Iteratively refine bat positions, mimicking the echolocation process and progressively enhancing the chances of identifying an optimal feature subset.

Termination by Convergence (End of Echolocation): Continue iterations until a predefined convergence criterion is met or a specified number of iterations is completed. The final bat positions represent the optimized feature subsets.

c) Genetic Algorithm (GA): The Genetic Algorithm (GA) [29] introduced the idea of using a population-based search inspired by biological evolution to solve optimization problems. The concept has since evolved, and various adaptations of genetic algorithms have been proposed and applied to different domains, including feature selection in machine learning.

The Genetic Algorithm (GA) comprises the following key steps:

Initialization: Generate an initial population of potential solutions, each representing a binary feature subset.

Evaluation: Assess the fitness of each solution based on a fitness function, evaluating its performance with the selected features.

Selection: Choose individuals from the population to act as parents for the next generation, favoring those with higher fitness.

Crossover (Recombination): Combine genetic material from selected parents to create new offspring.

Mutation: Incorporate minor random alterations to select individuals to uphold genetic diversity.

Replacement: Substitute a portion of the current population with the newly generated offspring.

Termination Criteria: Verify if a termination criterion has been satisfied, which could entail reaching a maximum number of generations or attaining a designated fitness threshold.

Result Extraction: Extract the final chromosome or feature subset from the population as the optimized set of features.

D. Machine Learning Algorithms

1) Dynamic Ensemble Selection Models (DES): are a promising and relevant technique belonging to the category of MCS approaches. Using base classifiers, they dynamically choose the most skilled classifiers for every new test item being classified, with each classifier being competent in a local 'feature space' region. These approaches have shown superior results compared to traditional ensemble methods that combine the results of base classifiers.

a) META-DES (Dynamic Ensemble Selection using Meta-Learning): [30] is a machine learning algorithm designed for dynamic ensemble selection in the field of classification. Its main objective is to approach classification dynamically by treating it as a meta-problem involving determining whether a particular classifier, chosen from a set of classifiers, is competent enough to accurately classify specified test data. This process involves two main steps. First, meta-features such as a posteriori probability for every label, the classifier's overall local accuracy, a vector indicating the difficulty of classifying neighboring instances, and the classifier's confidence based on the perpendicular distance separating the input sample from its decision boundary are derived. Subsequently, meta-classifiers exploit these meta-features to predict the ability of the selected classifier to provide accurate predictions for the designated test data. The classifiers identified by the meta-classifiers are then merged to construct a set of classifiers for the specified test data. META-DES essentially adopts a meta-perspective on classification, striving to dynamically choose the best-performing classifiers for a particular task, based on extracted meta-features.

b) DESP (Dynamic Ensemble Selection with Probability): [31] is an algorithm designed for dynamically selecting the best classifiers from an ensemble by eliminating those deemed incompetent. This is done by evaluating the performance of a single classifier against a random one. The performance given by the random classifier is determined by taking 1/M, with M being defined as the total number of classes that exist in the dataset. Classifiers are dynamically selected for each test data set on the basis of their performance relative to the performance achieved by the random neighborhood classifier selected for the test data set. If the performance of a classifier outperforms the random one, it is deemed suitable for selection into the ensemble for this particular test data set. If no classifier is selected, all classifiers in the ensemble are chosen for the given test dataset. In summary, the algorithm aims to create a dynamic ensemble of classifiers by eliminating incompetent ones and favoring those with better performance than a random classifier in a specified neighborhood.

c) KNORA-U (K-Nearest-Neighbor Algorithm for Dynamic Classifier Selection): The KNORAU algorithm, as outlined in [32], is designed to enhance the accuracy of classifying test samples. It utilizes the concept of k-nearest neighbors (KNN) by identifying the K closest neighbors for each test sample based on distances in feature space. KNORAU then selects classifiers from the initial pool that have accurately classified at least one neighbor among the K nearest, thereby forming a sample-specific ensemble. The prediction of the test sample's label employs the majority vote rule within this ensemble, with vote weights determined by each classifier's past performance in the K-nearest neighborhood. In essence, KNORAU strategically leverages classifier performance within the vicinity of the K-nearest neighbors to improve classification accuracy.

d) Dynamic Ensemble Selection KNN (DESKNN): The DES-KNN method, as introduced in [33], is an ensemble classifier selection algorithm aimed at identifying an optimal set from an initial group of classifiers. It employs diversity and accuracy as selection criteria. Initially, the algorithm identifies the most accurate classifiers within the competence region of a given test dataset. It then proceeds to select the most diverse classifiers among the most accurate ones using a measure known as the double-fault measure. Percentage-based selection, informed by prior research, dictates the proportion of classifiers chosen based on their accuracy and diversity. These percentages have been determined based on the superior performance observed in previous studies.

e) KNORA-E (K-Nearest-Neighbor Algorithm for Ensemble): [32] is a dynamic ensemble selection approach. It aims to choose a set of classifiers from a pool that can accurately classify all K nearest neighbors in a test dataset within a specific training set. The selection process is dynamic, eliminating classifiers that fail to classify at least one nearest neighbor correctly. Once the classifier set is identified, it is used for majority voting in subsequent classifications, following the majority voting rule. If an ensemble isn't found with the initial K value, KNORAE progressively adjusts the K value downward until at least one classifier set is identified. In summary, KNORAE, based on DES, seeks to select a robust set of classifiers capable of correctly classifying the nearest neighbors of a test point within a specific training set.

f) Multiple-Classifier Behavior (MCB): The MCB method[34] involves determining the competence region of a new test sample using the behavioral knowledge space (BKS) and the accuracy of the local classifier. Output profiles are generated for the test sample and its competence region. The similarity between the output profiles of the test sample and those of its skill region is measured. Samples with similarities below a specified threshold are ignored, allowing the size of the proficiency region to be adjusted. The skill of the base classifier is assessed on the basis of its classification accuracy in this adjusted skill region. If a selected classifier has a significant performance advantage over the others (with a difference in skill exceeding a predetermined threshold), it is used for classification. Alternatively, all classifiers are then combined using the majority vote rule.

g) k-Nearest Output Profiles (KNOP): The KNOP method[35] consists of the selection of classifiers that have classified one or more samples within the expertise area of the sample being queried. The region of competence is determined by analyzing the decisions made by the base classifier, known as output profiles. Rather than considering the feature space, the degree of similarity that exists between the queried sample and the validation sample is evaluated through the decision space. Every classifier chosen is allocated a number of votes equivalent to the actual number of samples in the skill region where it accurately predicts the label. The cumulative votes of all core classifiers are then combined to produce the final ensemble decision.

IV. Results

A. Performance Evaluation Metrics

In our evaluation of the proposed approach, we gauge its performance using essential performance metrics. Accuracy assesses the overall correctness of a classification model by comparing correctly predicted instances to the total. Precision quantifies the relevance of positive predictions, while recall evaluates the model's capability to identify actual positives. AUC (Area Under the ROC Curve) serves as a binary classification metric, representing the area under the curve that plots the true positive rate against the false positive rate at various thresholds.

a) Accuracy: Accuracy stands as a prevalent evaluation metric utilized to assess the overall performance of a classification model. It denotes the ratio of correctly predicted instances to the total number of instances within the dataset.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Instances}}$$

b) Precision: Precision serves as a metric that quantifies the proportion of true positive predictions out of all positive predictions made by the model. It offers a measure of how many of the predicted positive instances are indeed relevant.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}}$$

c) Recall (Sensitivity or True Positive Rate): The recall, also referred to as sensitivity or true-positive metric, evaluates the ratio of true-positive instances that are correctly classified by the model.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}}$$

d) AUC (Area Under the Receiver Operating Characteristic Curve): AUC, commonly used for binary classification problems, is a performance metric that represents the area under the receiver operating characteristic (ROC) curve. The ROC curve plots the true positive rate against the false positive rate at various threshold levels.

The AUC is calculated by integrating the ROC curve:

$$\text{AUC} = \int \text{TPR}(\text{FPR})\, d\text{FPR}$$

e) F1-score (F1-measure): The F1-score is a measure of a model's accuracy, balancing both precision and recall.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

B. Machine Learning Models Analysis

In this section, we delve into the analysis of the performance of various dynamic ensemble selection methods for the classification and prediction of Multiple Organ System Dysfunction (MODS) using vital signs from the initial 12 hours in the Intensive Care Unit (ICU). Experiments were conducted on a computer with an Nvidia GeForce MX 350 graphics card, an Intel Core i7-10700T processor, and 16 GB of RAM based on scikit-learn 1.1.2 in Python 3.10.8.

We conducted four experiments, each in search of the combination of the best classifier and the most efficient feature selection method for MODS prediction, respectively. Our approach involved testing various state-of-the-art dynamic ensemble models with and without bio-inspired feature selection methods. Model selection was based mainly on comparing their performance statistically. As shown in Fig. 7, four distinct results were reported for the tested models: without feature selection as shown in Fig. 7d, with the genetic algorithm as shown in Fig. 7a, with the binary bat algorithm as shown in Fig. 6b, and with the grey wolf optimization as shown in Fig. 7c.

The dataset was split into two subsets: 70% for training and 30% for testing. The training set was utilized to perform optimization and training of baseline classifiers using cross-validation, while the test set was used to evaluate the performance of dynamic ensemble selection (DES) models based on various metrics.Seven state-of-the-art DES models were applied: META-DES, DESP, KNORA-U, DESKNN, KNORA-E, MCB and KNOP. In addition, three bio-inspired feature selection algorithms were used to identify the most appropriate feature subset: GWO, BBA and GA. The models were applied to both the entire feature set and the selected features.

a) Analysis of Results using All Features: In this section, we investigate the performance of dynamic ensemble models with full features. Table III provides details of the results achieved by the ML models on several evaluation measures. We summarise the results as follows: Using DESKNN and KNOP with full feature sets produced minor

TABLE III. Performance Metrics for Ensemble Models with Different Feature Selection Techniques

Ensemble Models	Feature Selection	Accuracy	Precision	Recall	F1	AUC
KNORA-E	GWO	**0.945**	**0.933**	**0.957**	**0.945**	**0.973**
	BBA	0.853	0.951	0.741	0.833	0.864
	GA	0.906	0.942	0.863	0.901	0.915
	Without FS	0.926	0.943	0.905	0.924	0.965
METADES	GWO	**0.965**	**0.972**	**0.957**	**0.964**	**0.984**
	BBA	0.915	0.934	0.891	0.912	0.959
	GA	0.89	0.927	0.843	0.883	0.935
	Without FS	0.936	0.944	0.927	0.936	0.973
KNORA-U	GWO	**0.942**	**0.929**	**0.957**	**0.943**	**0.971**
	BBA	0.84	0.916	0.744	0.821	0.867
	GA	0.902	0.929	0.868	0.898	0.917
	Without FS	0.915	0.922	0.905	0.913	0.964
DESKNN	GWO	**0.94**	**0.924**	**0.957**	**0.94**	**0.968**
	BBA	0.836	0.907	0.744	0.817	0.871
	GA	0.898	0.922	0.868	0.894	0.909
	Without FS	0.891	0.869	0.92	0.894	0.951
MCB	GWO	**0.94**	**0.93**	**0.949**	**0.94**	**0.967**
	BBA	0.837	0.91	0.744	0.818	0.863
	GA	0.898	0.922	0.868	0.894	0.896
	Without FS	0.909	0.906	0.912	0.909	0.955
DESP	GWO	**0.934**	**0.927**	**0.939**	**0.933**	**0.978**
	BBA	0.838	0.913	0.744	0.82	0.852
	GA	0.898	0.922	0.868	0.894	0.909
	Without FS	0.915	0.932	0.894	0.912	0.962
KNOP	GWO	**0.941**	**0.928**	**0.954**	**0.941**	**0.974**
	BBA	0.835	0.897	0.751	0.818	0.869
	GA	0.873	0.875	0.868	0.871	0.917
	Without FS	0.886	0.86	0.92	0.889	0.951

performance (accuracy=0.891, precision=0.869, recall=0.92, F1-score=0.894, and AUC=0.951) and (accuracy=0.886, precision=0.86, recall=0.92, F1-score=0.889, and AUC=0.951), respectively.MCB , DESP and KNORA-U improved their performance by approximately 3% compared with KNOP. KNORA-E improved its performance by approximately 1.1% compared with KNORA-U. The highest performance was achieved with METADES (accuracy = 0.936, precision = 0.944, recall = 0.927, F1 score = 0.936 and AUC = 0.973). Fig. 6d depicts the AUC and ROC curves of the models with full features. The METADES model achieves the highest AUC (0.973), while the KNOP model achieves the lowest AUC (0.951). Fig. 7d shows the radar plot for models with full features, and places the METADES model in the outperforming category.

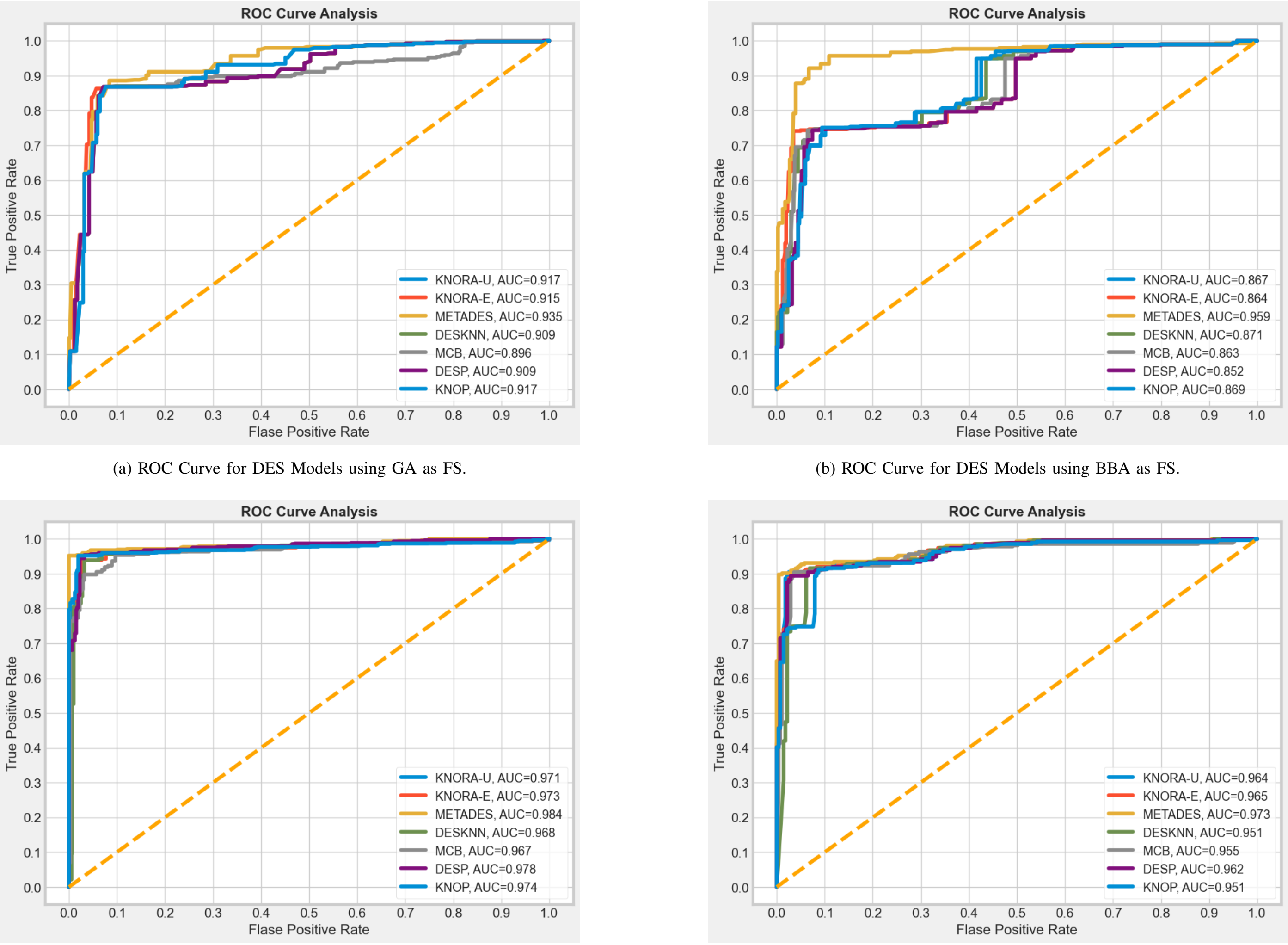
b) Results Analysis using the Grey Wolf Optimization (GWO) for Feature Selection: In this section, we investigate the performance of the Ensemble Dynamic Models with selected features by the GWO. Table III provides details of the results achieved by the ML models on several evaluation measures. We summarise the results as follows: Using DESP with selected feature sets produced minor performance (accuracy = 0.934, precision = 0.927, recall = 0.939, F1-score = 0.933 and AUC = 0.978) . MCB and DESKNN improved performance with about 0.6% above DESP. KNORA-U and KNORA-E improved their performance by approximately 0.2-0.3% above MCB and DESKNN. The highest performance was achieved with METADES (accuracy=0.965, precision=0.972, recall=0.957, F1-score=0.964, and AUC=0.984). Fig. 6c depicts the AUC and ROC curves of the models with selected features by GWO. The METADES model achieves the highest AUC =0.984, while the MCB model achieves the lowest AUC (0.967). Fig. 7c shows the Radar Plot of the models with selected features by GWO and places the METADES Model in the outperforming category.

c) Results Analysis using the Binary Bat Algorithm (BBA) for Feature Selection: In this section, we investigate the performance of the Ensemble Dynamic Models with selected features by the BBA. Table III provides details of the results achieved by the ML models on several evaluation measures. We summarise the results as follows: Using KNOP and DESKNN with selected feature sets produced minor performance (accuracy=0.835, precision=0.897, recall=0.751, F1-score=0.818, and AUC=0.869) and (accuracy=0.836, precision=0.907, recall=0.744, F1-score=0.817, and AUC=0.871), respectively. MCB and DESP improved performance by about 0.1–0.2% above KNOP and DESKNN. KNORA-U and KNORA-E improved their performance by approximately 1.6% above KNOP and DESKNN. The highest performance was achieved with METADES (accuracy=0.915, precision=0.934, recall=0.891, F1-score=0.912, and AUC=0.959). Fig. 6b depicts the AUC and ROC curves of the models with selected features by BBA. The METADES model achieves the highest AUC of 0.959, while the DESP model achieves the lowest AUC of 0.852. Fig. 7b shows the Radar Plot of the models with selected features by BBA and places the METADES Model in the outperforming category.

d) Results Analysis using the Genetic Algorithm (GA) for Feature Selection: In this section, we investigate the performance of the Ensemble Dynamic Models with selected features by the GA. Table III provides details of the results achieved by the ML models on several evaluation measures. We summarise the results as follows: Using KNOP with selected feature sets produced minor performance (accuracy = 0.873, precision = 0.875, recall = 0.868, F1-score = 0.871, and AUC = 0.917). METADES improved their performance by approximately (1.7)% above KNOP and DESKNN, MCB and DESP improved performance by about 0.8% above METADES, and KNORA-U improved performance by about 0.22% above DESKNN, MCB, and DESP. The highest performance was achieved with KNORA-E (accuracy=0.902, precision=0.929, recall=0.868, F1-score=0.898, and AUC=0.917). Fig. 6a depicts the AUC and ROC curves of the models with selected features by GA. The METADES model achieves the highest AUC (0.935), while the MCB model achieves the lowest AUC (0.896). Fig. 7a shows the Radar Plot of the models with selected features by GA and places the KNORA-E Model in the outperforming category.

e) Comparison Between All Models: In this paper, we investigate the performance of dynamic ensemble models utilizing all features as well as features selected using bio-inspired feature selection algorithms. As shown in Table III, a confusion matrix in Fig. 8 is used to depict and display the performance of dynamic ensemble models using GWO as a feature selection technique and to give an overview of the model's classification errors. The METADES model with GWO as feature selection technique achieved the highest performance compared to both complete features and features selected by GA and BBA, with an accuracy of 96.5%,a precision of 97.2%, a recall of 95.7%, an F1-score of 96.4%, and an AUC of 98.4%. Conversely, the METADES model with GA-selected features demonstrated the lowest performance.

These findings emphasize the effectiveness of the approach using the METADES model and the GWO feature selection method in predicting patients at risk of developing MODS, suggesting its potential for clinical application.



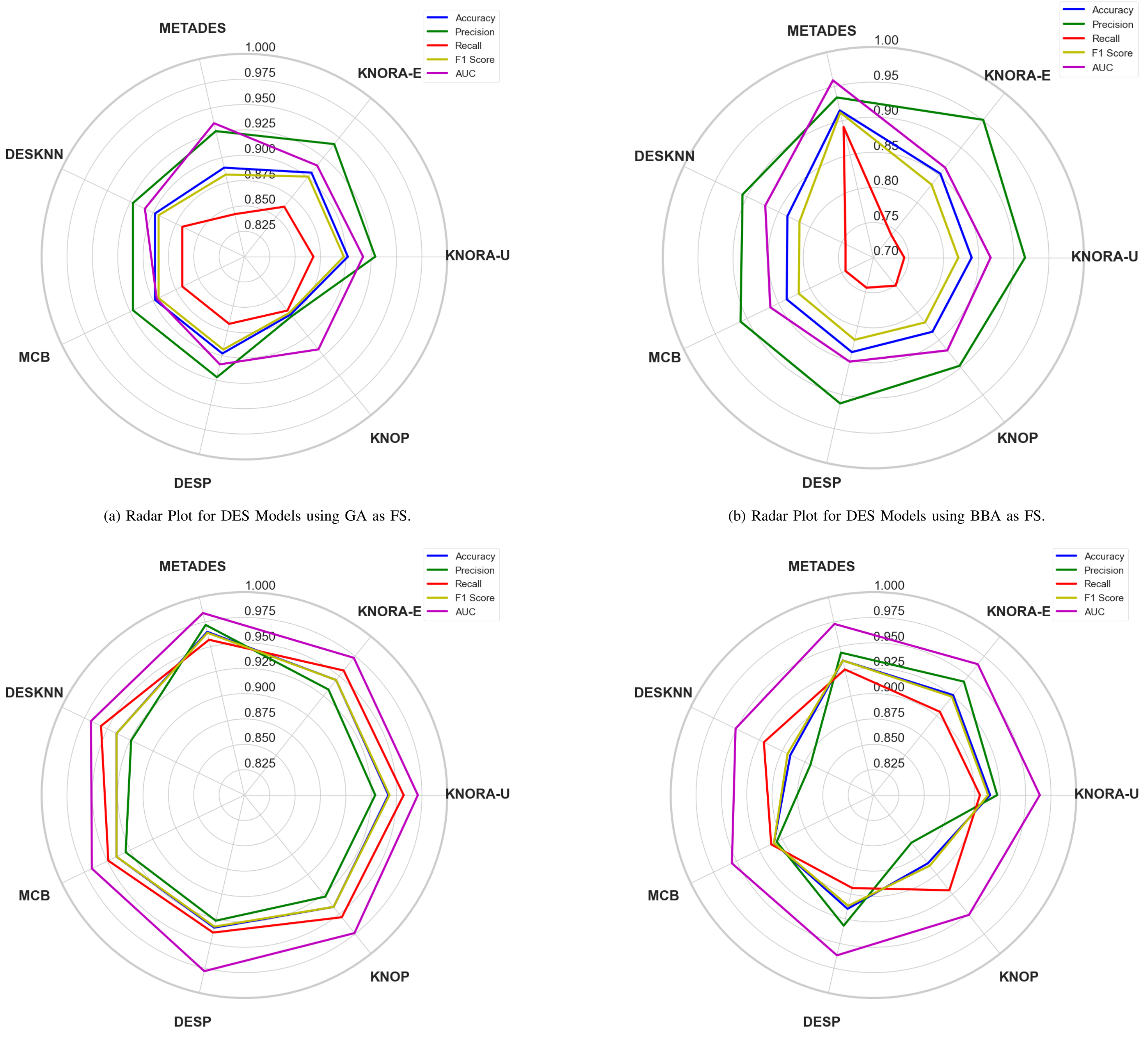
(a) ROC Curve for DES Models using GA as FS.

(b) ROC Curve for DES Models using BBA as FS.

(c) ROC Curve for DES Models using GWO as FS.

(d) ROC Curve for Dynamic Ensemble Models without Feature Selection.

Fig. 6. ROC curves of dynamic ensemble models with and without feature selection techniques.



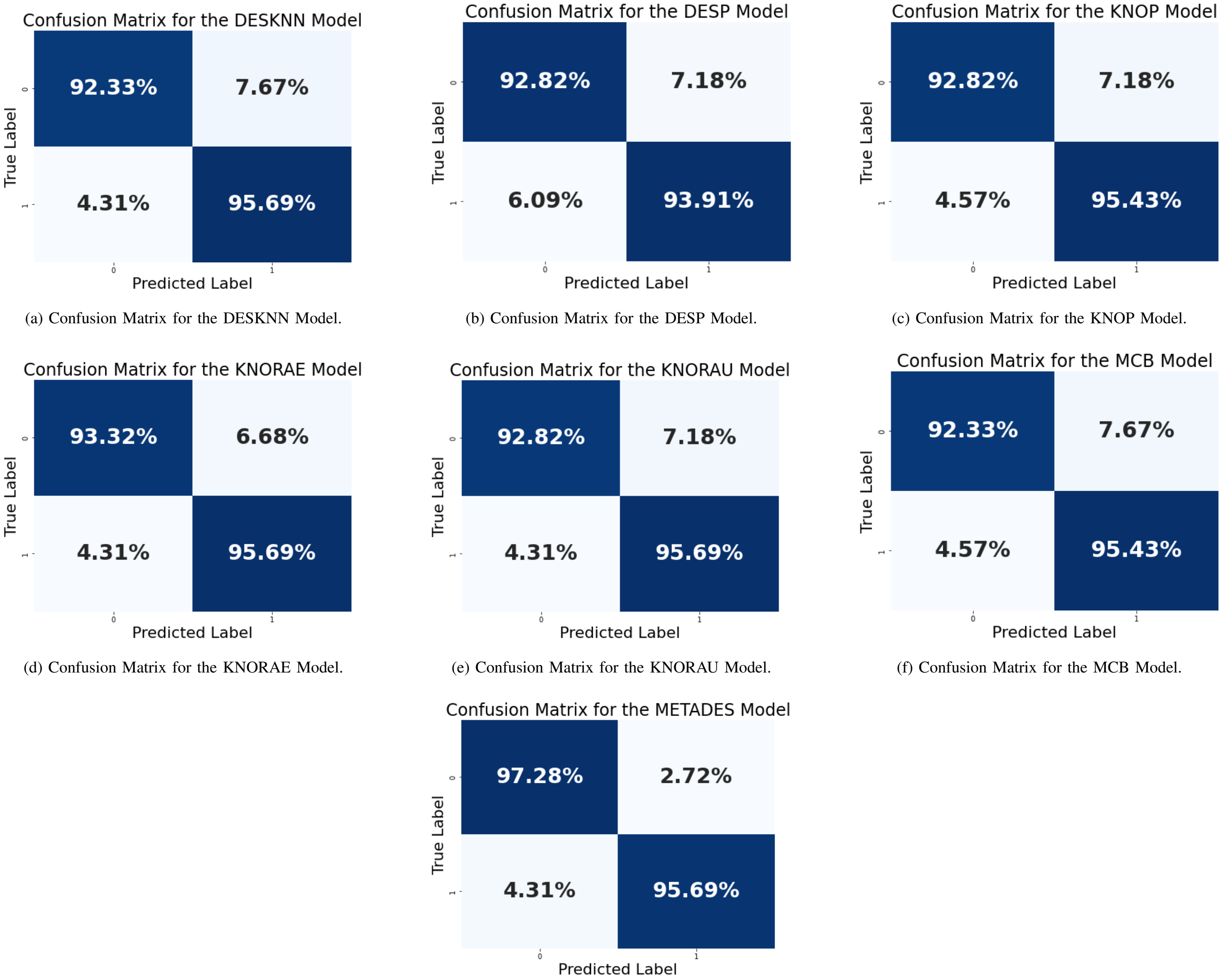
(a) Radar Plot for DES Models using GA as FS.

(b) Radar Plot for DES Models using BBA as FS.

(c) Radar Plot for DES Models using GWO as FS.

(d) Radar Plot for Dynamic Ensemble Models without Feature Selection.

Fig. 7. Radar plots of dynamic ensemble models with and without feature selection techniques.



(a) Confusion Matrix for the DESKNN Model.

(b) Confusion Matrix for the DESP Model.

(c) Confusion Matrix for the KNOP Model.

(d) Confusion Matrix for the KNORAE Model.

(e) Confusion Matrix for the KNORAU Model.

(f) Confusion Matrix for the MCB Model.

(g) Confusion Matrix for the METADES Model.

Fig. 8. Confusion matrix for dynamic ensemble models using GWO as feature selection techniques.

V. Limitations and Future Directions

Although our proposed approach is promising for the early prediction of MODS in the ICU, it has certain limitations: Firstly, the dataset used in this study includes only MIMIC III patients, specifically those admitted to the intensive care units (ICUs) of Beth Israel Deaconess Medical Center in Boston, Massachusetts, USA. To ensure the generalizability of the model, we are planning to test it with other real-world datasets. Secondly, although dynamic ensemble models outperform deep learning models in terms of speed, the use of time-series datasets using deep learning methods such as LSTM and CNN may enhance performance. Thirdly, to be clinically accepted as a decision-support system, the approach must be interpretable. For this reason, we plan to study various methods of explainability, such as eXplainable Artificial Intelligence (XAI). Future studies will address all these limitations.

VI. Conclusion

In this work, we proposed a decision support system for the early prediction of Multi-Organ Dysfunction Syndrome (MODS) in the intensive care unit (ICU). Utilizing only non-invasive features and time-series records gathered from the initial 12 hours of admission in the ICU, the system aimed to support doctors by accelerating their decision-making process. We explored the effectiveness of dynamic ensemble selection models in predicting the risk of developing MODS within the ICU. We compared the performance of models with full features and with feature selection methods, evaluating three nature-inspired metaheuristic optimization feature selection techniques: the binary bat algorithm (BBA), grey wolf optimization (GWO), and genetic algorithm (GA) in order to select the optimal feature subset.

The proposed system was trained and evaluated on a cohort of 1,392 patients extracted from the MIMIC III dataset. The METADES model with GWO as the feature selection technique achieved the highest performance compared to models using all features or features selected by other methods. It demonstrated an accuracy of 96.5%, a precision of 97.2%, a recall of 95.7%, an F1-score of 96.4%, and an AUC of 98.4%. Conversely, the METADES model with GA-selected features exhibited the lowest performance.

These findings highlighted the effectiveness of our approach using the METADES model and the GWO feature selection method in predicting patients at risk of developing MODS, suggesting its promising potential for clinical application.

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Cephalometric Landmarks Identification Through an Object Detection-based Deep Learning Model

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Abstract—**In the field of orthodontics, the accurate identification of cephalometric landmarks in dental radiography plays a crucial role in ensuring precise diagnoses and efficient treatment planning. Previous studies have demonstrated the impressive capabilities of advanced deep learning models in this particular domain. However, due to the ever-changing technological landscape, it is imperative to consistently investigate and explore emerging algorithms to further improve efficiency in this field. The present study centers around the assessment of the effectiveness of YOLOv8, the most recent version of the 'You Only Look Once (YOLO)' algorithm series, with a particular emphasis on its autonomous capability to accurately identify cephalometric landmarks. In this study, a thorough examination was conducted to evaluate the YOLOv8 algorithm efficiency in detecting cephalometric landmarks. The assessments encompassed various aspects such as precision, adaptability in challenging conditions, and a comparative analysis with alternative algorithms. The predefined proximities of 2mm, 2.5mm, and 3mm were utilized for the comparisons. By focusing on its potential as a noteworthy breakthrough, the investigation seeks to ascertain whether the recent enhancements indeed bring about a significant stride in the precise identification of cephalometric landmarks.**

Keywords*—*Cephalometry; YOLOv8; landmark detection; orthodontics

I. Introduction

Since its introduction by Broadbent in 1931, the cephalometer has garnered extensive recognition as a universally adopted diagnostic instrument within the realms of orthodontic practice and research [1]. Cephalometry, a field of study focused on the measurement of cranial dimensions, involves the meticulous quantification of these dimensions using either direct measurements or radiographic techniques. This process involves identifying specific anatomical landmarks as reference points for accurate and standardized measurements. The incorporation of suitable standards plays a pivotal role in the assessment of facial growth and development, rendering them an indispensable component in the diagnostic and treatment planning stages of orthodontics. In the realm of cephalometrics, the arduous task of manually identifying and annotating cephalometric landmarks on radiographic images has long been entrusted to proficient experts in the field. Hand annotation, while a valuable technique, is known for its labor-intensive nature and vulnerability to human error-induced discrepancies [2] [3].

The advent of deep learning in the field of medical imaging has brought about a profound transformation in various diagnostic techniques, such as cephalometric analysis. In this emerging era of digital diagnostics, machine learning algorithms have taken the lead, paving the way for significant advancements in orthodontic diagnostic practices and treatment strategies. Prior research has clarified the impressive potential of deep learning models in automating this critical procedure, resulting in significant improvements in both precision and speed.

In the domain of diagnostic automation, deep learning has witnessed remarkable progress. However, the quest for enhanced speed, better precision, and unwavering reliability remains unyielding. Our research is conducted within the context of an ongoing pursuit of continuous improvement.

In this study, we aim to evaluate the capabilities of YOLOv8, the most recent version of the renowned "You Only Look Once (YOLO)" models, in the realm of automated cephalometric landmark detection. This inquiry transcends pure theory and holds significant practical implications for the field of orthodontics. Previous studies have highlighted its potential, but a comprehensive exploration of its performance, especially in diverse clinical scenarios, remains lacking [4].

In our investigation, we delve into the intricate details of YOLOv8, meticulously examining its precision, speed, and robustness metrics. Simultaneously, we remain vigilant in assessing its practicality and suitability for real-world orthodontic clinical scenarios. Our main goal in this study is to find out how well YOLOv8 can bridge the gap between extremely advanced technology and the practical needs of orthodontic practice, setting new standards in the field that have never been seen before.

In this article, we will start by elucidating the underlying impetus behind our research, thereby furnishing a lucid comprehension of the motivation that propelled this work forward. In the subsequent sections, we shall embark on an in-depth examination of pertinent literature, thereby furnishing crucial background information for our research endeavor.

In the sections that follow, we will talk about all of our materials and methods in detail, including the organized way we gathered data, how carefully we prepared it, and how strictly we followed our training procedures. In this section, we will delve into the intricate methods utilized, providing a thorough understanding of the meticulous approach undertaken during the research endeavor.

In the upcoming parts, we will give the results obtained from our thorough inquiry, offering a concise summary of the findings acquired from our analysis of data and experimentation. In the last part of this essay, we will conduct a thorough examination, combining the results, extracting meaningful observations, and possibly suggesting avenues for further research.

II. Motivation

In the field of medical diagnostics, the importance of cephalometry cannot be emphasized enough. The field of craniofacial imaging has played a vital role in the medical industry for many years. Its significance lies in its ability to diagnose craniofacial malformations, facilitate detailed surgical planning and evaluation, and contribute to essential growth studies. Cephalometry, a field of study focused on craniofacial analysis, centers around the meticulous identification of craniofacial landmarks. This crucial process involves the precise detection of cephalometric landmarks on the cephalogram, serving as the fundamental initial stage in conducting any cephalometric analysis [5] [6] [7]

In the past few years, the field of deep learning has witnessed the emergence of highly sophisticated models that have demonstrated exceptional capabilities in this particular domain [8] [9] [10]. The advent of these models has brought about a paradigm shift in the field, presenting ingenious approaches to tackle the complex challenge of landmark identification. In light of the ever-changing technological terrain, it is crucial to consistently delve into and scrutinize nascent algorithms. The need to maximize efficiency and precision fuels the relentless pursuit of advancement in cephalometric analyses.

In our relentless quest for perfection, we embarked on a comprehensive exploration of the most recent breakthroughs in the realm of object detection. In our study, we sought to enhance the accuracy and efficiency of cephalometric landmark identification by harnessing the advanced capabilities of the YOLOv8 algorithm. This algorithm has gained widespread recognition for its exceptional performance in detecting objects. The YOLOv8 model distinguishes itself in the field of computer vision with its remarkable precision and efficiency. The model's exceptional performance is a result of meticulous training on an extensive and varied dataset, ensuring its ability to handle diverse visual scenarios.

The utilization of cephalometry in the medical field is of utmost importance, and with the constant advancements in technology, our investigation of YOLOv8 marks a significant leap forward. Through the utilization of this cutting-edge algorithm, our objective is to not only augment the accuracy of cephalometric landmark detection but also make substantial contributions to the continuous progress in medical diagnostics.

The motivation behind this research was clearly defined in this part. In the following section, we will conduct a thorough examination of the pertinent literature in the topic, providing useful insights into the existing body of knowledge.

III. Related Works

In the field of orthodontics, the convergence of cutting-edge machine learning and computer vision, specifically through the utilization of deep learning techniques, presents a remarkable opportunity for an upheaval. The precise diagnosis of cephalometric landmarks can be significantly improved through the implementation of automated detection techniques [11].

In the realm of orthodontics, the lack of medical imaging data presents an immense barrier. However, the imperative for collaboration between orthodontic professionals and skilled data scientists remains essential. The integration of specialized datasets and advanced techniques holds great potential in bridging the gap between deep learning algorithms and the intricacies of orthodontic imaging. The integration of advanced technologies in dental healthcare not only enhances the efficiency of diagnosis and treatment planning but also serves as a catalyst for innovation in the field [12].

Acknowledging the importance of automatic landmark detection, The ISBI, which stands for the International Symposium on Biomedical Imaging, has led the organization of a number of challenges related to the matter, namely in 2014 [13], in 2015 [14], and is set to continue its impact in the year of 2023 [15].

Over the past few decades, extensive research has been conducted on a multitude of automated techniques aimed at detecting landmarks. In first studies, Wang et al. [13] [14] spearheaded pioneering initiatives that involved the organization of public challenges. These challenges served as platforms to exhibit innovative algorithms that are at the forefront of scientific advancement. Researchers have successfully utilized random forests, a machine learning technique, to classify intensity appearance patterns with remarkable accuracy. Moreover, they have employed statistical shape analysis to gain insights into the complex spatial relationships among landmarks. This innovative approach has yielded impressive results, showcasing the potential of these cutting-edge techniques in various scientific domains.

In another study, Ibragimov and colleagues [16] have presented impressive findings by harnessing the power of Random Forest and Game Theoretic techniques. Researchers such as Chu et al. have successfully utilized tree-based methods in their studies. These methods include hierarchical random forest regression and binary pixel classification with randomized trees [17].

In same vein, Lee et al. and Arik et al. have made significant strides in the field of pixel classification by leveraging convolutional neural network (CNN) concepts. Their work has paved the way for the development of cutting-edge algorithms in this domain [18], [19]. Subsequent studies delved into the realm of deep learning, utilizing U-shaped deep convolutional neural network (CNN) structures to achieve accurate landmark estimation [20] [21].

Mehmet Ugurlu and Alshamrani Khalaf, two researchers, have achieved significant progress in the field of automated cephalometric landmark detection implementing an altered architecture known as the Feature Aggregation and Refinement Network (FAR Net) (Ugurlu, 2022) [22], and an Inception-based neural network layers [23].

In the upcoming chapter, we will conduct a thorough examination of the essential components of our research. This examination will comprehensively investigate the methodological framework that underpins our research. We will primarily concentrate on the specifics of our data gathering procedure, the methodology we have utilized, and the meticulous preparations undertaken for our training data.

IV. Materials

This chapter provides a comprehensive analysis of the complexities involved in our study technique. In the first stage of our study, we will provide a thorough examination of our data collection process, with a detailed explanation of the methods used and the sources of our data. The dataset is thoroughly documented, offering a strong foundation for our upcoming investigations.

After the comprehensive discussion on the process of data acquisition, we now delve into the intricate preparations that were meticulously carried out to enhance the quality of our dataset for the purpose of training. The methodology encompasses various essential components, such as preprocessing techniques, data cleansing methodologies, and necessary transformations implemented to guarantee the dataset's appropriateness for the intended research.

In the culmination of this chapter, we embark upon the fundamental essence of our investigation—the proposed methodology. In this article, we will explore the cutting-edge methodologies and techniques that underpin our research efforts. By the conclusion of this chapter, readers will have acquired a thorough comprehension of the meticulous procedures and approaches that form the foundation of our research methodology.

A. Data Acquisition

In a meticulous and all-encompassing investigation, a collection of lateral cephalograms was procured from a heterogeneous group consisting of 400 individuals. The subjects covered a wide age range, from 7 to 76 years, with an average age of 27.0 years. The sample comprised 235 females and 165 males, ensuring a balanced representation of both genders. The cutting-edge Soredex CRANEXr Excel Ceph machine, situated in Tuusula, Finland, was employed to capture all images in the TIFF format. These images were subsequently processed using the advanced Soredex SorCom software, specifically versions 3.1.5 and 2.0. The captured images exhibited an impressive resolution of 1935×2400 pixels, accompanied by a pixel spacing of 0.1mm, thereby guaranteeing an exceptional level of precision and meticulousness in capturing even the finest details [24]. The dataset utilized in this study, sourced from the ISBI 2015 challenge, consisted of distinct collections of data obtained from a total of 400 subjects. Each subject's data encompassed a lateral cephalogram, as well as two sets of landmark points that were meticulously plotted by skilled orthodontic specialists. Notably, both a junior and a senior specialist contributed to the manual plotting of these landmark points. Significantly, the average intra-observer variability for these specific landmarks was found to be 1.73 mm and 0.90 mm, respectively, indicating a high level of precision [19]. In the captured images, every individual pixel corresponded to a precise 0.1 mm square region. These pixels were characterized by grayscale values spanning from 0 to 255. In order to ensure a good training phase, a total of 150 images were subjected to augmentation techniques, the test1 set was merged to the training set, resulting in an increase to over 900 images. These augmented images were then carefully allocated for rigorous training purposes. Additionally, the remaining 100 images underwent meticulous testing. This comprehensive approach provided a robust assessment of the overall performance of the system. See the annotated image below in Fig. 1.

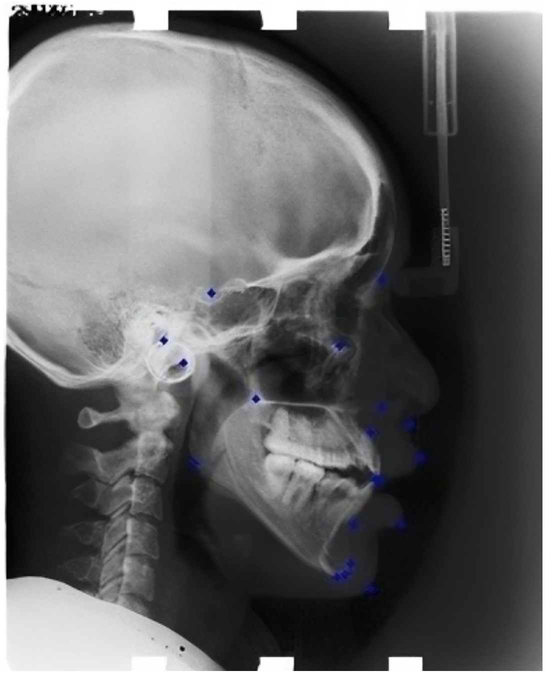

Fig. 1. Annotated image.

B. Data Preparation

In the pursuit of scientific inquiry, we diligently undertook a comprehensive analysis of the data preparation phase, breaking it down into various discrete stages. This approach diverged significantly from the methodologies employed in previous studies. In our study, we departed from traditional methodologies and instead, we embraced a simultaneous detecting approach across all data points.

The dataset being examined, as previously discussed, was burdened with limitations due to its size. In order to overcome these limitations, the incorporation of data augmentation techniques became crucial (Fig. 2). In our study, we have discovered that while mosaic augmentation possesses inherent advantages within the framework of YOLOv8, it unfortunately falls short in meeting our specific requirements. In pursuit of enhancing the dataset, our research endeavors prompted us to extract supplementary images from our preexisting repository of unprocessed visual data.

In the quest for enhancing data quality, we employed three pivotal techniques for augmentation. Color jittering has emerged as a powerful tool that is widely employed in the fields of computer vision and image processing. Through the intentional introduction of controlled randomness into the color attributes, our augmented dataset has successfully attained a heightened level of diversity, in term of saturation,contrast, brightness, and hue. The process of diversification has played a crucial role in enabling machine learning models to adapt and generalize effectively across a wide range of real-world situations. This adaptability is particularly evident in the models' ability to handle changes in lighting conditions and variations in color.

Furthermore, our study carefully utilized Gaussian noise, a fundamental augmentation technique deeply rooted in the fields of machine learning and computer vision. Through the careful manipulation of noise intensity and the introduction of stochastic perturbations into the input data, our augmentation methodology has successfully attained a remarkable level of precision. This includes the ability to accurately account for subtle differences in lighting conditions and address inaccuracies in sensor measurements.

Moreover, we used another technique on the experimental procedure, Random contrast, which involved the manipulation of image contrast through the expansion or compression of the range of pixel intensity values. The process of diversification played a crucial role in effectively addressing the challenge of analyzing images taken under different lighting conditions. By incorporating this approach, our model was able to successfully adapt to and manage the diverse levels of contrast encountered in various real-world situations. The implementation of random contrast adjustment has resulted in a notable improvement in the robustness of our model.

Another crucial aspect of our data preparation process was the transformation of labels. The recorded labels, originally in the form of coordinate dataframes, underwent a transformation to conform to the YOLO annotation format. The utilization of this particular format offers an additional advantage in the form of its inherent normalization feature. The successful outcome of this endeavor led to the smooth incorporation of our image data into the system, eliminating the necessity for additional adjustments such as resizing, scaling, or normalization procedures. The incorporation of this particular aspect has demonstrated itself to be a significant time-saving element within our data preparation procedure.

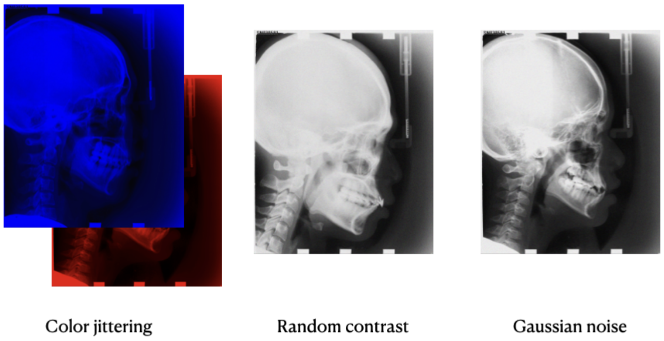

Fig. 2. Data augmentation.

V. Experimental Results

After establishing the underlying motivation behind our research and presenting a thorough summary of the existing literature in the field, we now proceed to explore the core aspects of our study. In this section, we introduce our proposed methodology that centers around leveraging the advanced functionalities of the most recent release of the state-of-the-art object detection algorithm, YOLOv8. Present the experiment's results, and conclude with a comparison with relevant findings from the previous studies.

A. The Proposed Approach

In our study, we adopted YOLOv8 as the base model, employing a meticulous approach to effectively tackle the complexities inherent in our research goals. The decision to utilize this particular choice was driven by its well-documented track record of high efficiency, exceptional accuracy, and remarkable adaptability. These qualities render it an optimal platform for conducting our scientific investigations. In the subsequent sections, we expound upon the intricate intricacies of our methodology, shedding light on the alterations, advancements, and refinements we incorporated to customize YOLOv8 for the precise challenges presented by our research inquiries.

Prior methods frequently employed sliding windows coupled with a classifier, necessitating hundreds or thousands of iterations per image, or employed more refined techniques that divided the task into two steps. The initial phase would identify prospective regions containing objects (referred to as "regions of interest"), and the subsequent phase would evaluate the presence of objects in these proposed regions using a classifier. Our model, only requires a single pass of the network to perform the detection task.

The structure of our model consists of multiple essential components, as illustrated in Fig. 3. The Conv block, also known as the beginning block, is composed of a conv2d layer, batch normalization, and a SiLu activation function. The parameters for this function include the input channels (c1), output channels (c2), kernel size (k), and stride (s). The following block, referred to as the c2f block, comprises Conv blocks in which the generated feature maps are distributed between the bottleneck block and the concat block. The parameters for this block consist of c1, c2, the quantity of shortcuts (n), and a boolean value indicating the utilization of shortcuts. The third block, known as the Spatial Pyramid Pooling Fast (SPPF) block, combines a Convolutional (Conv) block with three Max pooling layers. Significantly, every resultant feature map is merged together prior to the completion of the Spatial Pyramid Pooling Function (SPPF). The parameters accepted by this block include c1, c2, n, and a shortcut indicator. The last component, known as the Detect block, consists of many Conv blocks that have two separate tracks—one for bounding box data and another for class data. The combination of these blocks is detailed in Table I and visually depicted in Fig. 3.

In the field of deep learning research, much attention is typically given to the design of model architecture. However, it is imperative to recognize the significant impact that training procedures. The neural network model used in our study had 295 layers, with a total of 25,867,321 parameters and 25,867,305 gradients. We meticulously adjusted a set of hyperparameters in order to get optimal performance. Mosaic augmentation was activated, which introduced a dynamic element to the training data by merging numerous pictures. To optimize the process, we utilized the AdamW optimizer with a designated learning

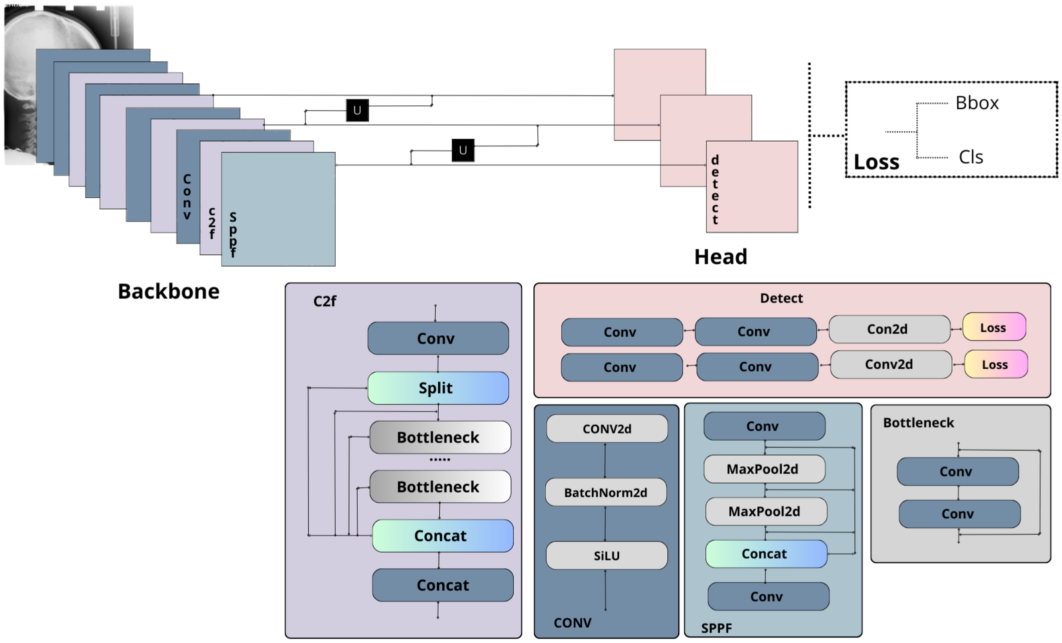

Fig. 3. YOLOv8 Architecture.

TABLE I. MODEL SUMMARY

Params per layer	Module Block	Arguments
1392	ultralytics.nn.modules.conv.Conv	[c1=3,c2= 48, k=3, s=2]
41664	ultralytics.nn.modules.conv.Conv	[c1=48, c2=96, k=3, s=2]
111360	ultralytics.nn.modules.block.C2f	[c1=96, c2=96, n=2, shortcut=True]
166272	ltralytics.nn.modules.conv.Conv	[c1=96, c2=192, k=3, s=2]
813312	ltralytics.nn.modules.block.C2f	[c1=192, c2=192, n=4, shortcut=True]
664320	ultralytics.nn.modules.conv.Conv	[c1=192, c2=384, k=3, s=2]
3248640	ultralytics.nn.modules.block.C2f	[c1=384, c2=384, n=4, shortcut=True]
1991808	ultralytics.nn.modules.conv.Conv	[c1=384, c2=576,k= 3, s=2]
3985920	ultralytics.nn.modules.block.C2f	[c1=576, c2=576, n=2, shortcut=True]
831168	ultralytics.nn.modules.block.SPPF	[c1=576, c2=576, k=5]
0	torch.nn.modules.upsampling.Upsample	[size=None, scale_factor=2, mode='nearest']
0	ultralytics.nn.modules.conv.Concat	[dimension=1]
1993728	ultralytics.nn.modules.block.C2f	[c1=960, c2=384, n=2]
0	torch.nn.modules.upsampling.Upsample	[size=None, scale_factor=2, mode='nearest']
0	ultralytics.nn.modules.conv.Concat	[dimension=1]
517632	ultralytics.nn.modules.block.C2f	[c1=576,c2= 192, n=2]
332160	ultralytics.nn.modules.conv.Conv	[c1=192, c2=192,k= 3, s=2]
0	ultralytics.nn.modules.conv.Concat	[dimension=1]
1846272	ultralytics.nn.modules.block.C2f	[c1=576, c2=384, n=2]
1327872	ultralytics.nn.modules.conv.Conv	[c1=384,c2= 384, k=3, s=2]
0	ultralytics.nn.modules.conv.Concat	[dimension=1]
4207104	ultralytics.nn.modules.block.C2f	[c1=960,c2= 576, n=2]
3786697	ultralytics.nn.modules.head.Detect	[nc=19, [192, 384, 576]]
Summary : 295 layers, 25867321 parameters, 25867305 gradients.		

rate of 0.000435, along with a momentum of 0.9. The training phase consisted of 60 epochs, with batches of size 20, which enhanced the overall resilience of the model.

After presenting a thorough clarification of the fundamental components of our methodology, our attention now shifts towards the results yielded by our endeavors. In the following sections, we shall now proceed to unveil the outcomes derived from the implementation of this particular methodology. The empirical evidence presented not only serves to confirm the strength and reliability of our methodology, but also provides valuable insights into the practical implications of our research in real-world scenarios. By conducting a meticulous examination and subsequent interpretation, we aim to elucidate the profound implications of these discoveries, effectively establishing a connection between theoretical knowledge and its real-world implementation.

B. Results

A distinctive feature of our research is the smooth integration of both unprocessed and meticulously enhanced data throughout the training stage of our YOLOv8 model. The combination of traditional imaging methods with augmented data has transformed the sector, presenting thrilling opportunities for enhanced precision and efficiency, ultimately resulting in notable progress in landmark detection. Our algorithm correctly recognized 19 anatomical landmarks on lateral cephalometric radiographs, proving its efficiency.

In order to assess the system's performance, we employed the Successful Detection Rate (SDR) score, a vital metric for quantifying its level of success. The SDR metric quantifies the accuracy of predicted landmarks by measuring the percentage of these landmarks that fall within a predetermined threshold distance from the ground truth.

Our system demonstrated exceptional performance in terms of average Successful Detection Rate (SDR) scores, operating within the specified range of 2 mm, 2.5 mm, and 3 mm. In the test set, the recorded scores were 86.31, 87.69, and 90.84, respectively. The findings show that the system's performance is consistently maintained throughout various settings, demonstrating its reliability and efficacy.

Through a rigorous examination of the data, a comprehensive analysis has unveiled captivating patterns that warrant further investigation. The 'S' point, scientifically referred to as Sella, the 'Po' point referring to the Pogonion, 'Gn' point and othres, has garnered significant attention due to the outstanding performance the model in prediction them in the threshold of 2mm.For other points, such as the lower lip, the precision of the model experienced a remarkable increase between the different thresholds, reaching a flawless 100.00 Successful Detection Rate within the specified thresholds of 2.5 mm and 3 mm, respectively. The Porion, A-point, and

Gonion point on the hand, have presented significant obstacles, according to the findings. The detection of these landmarks in lateral cephalometric radiographs has proven to be remarkably elusive, highlighting the complicated process of their identification (see Fig. 4 to 8).

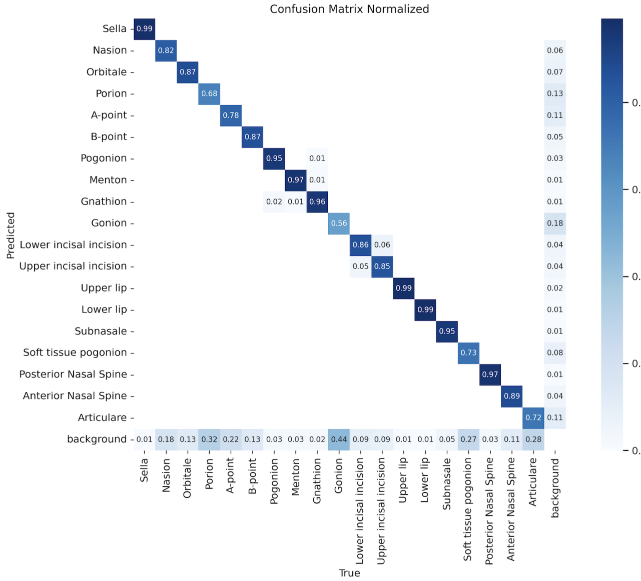

Fig. 4. Normalized confusion matrix for 2mm SDR.

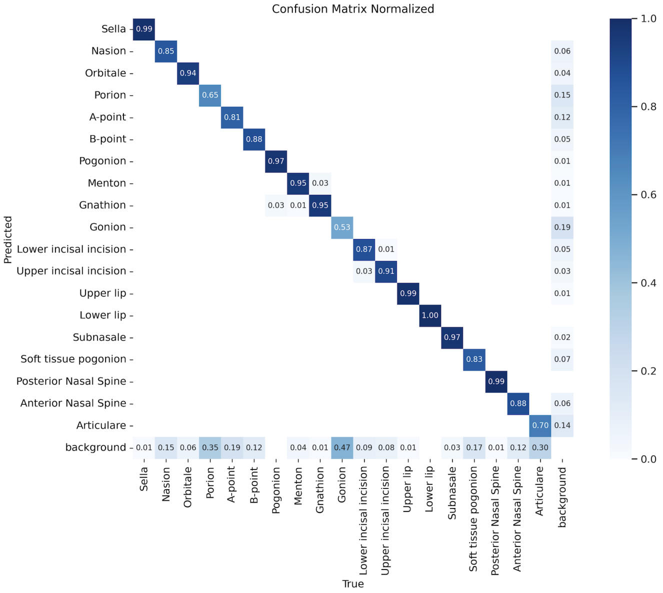

Fig. 5. Normalized confusion matrix for 2.5mm SDR.

To gain a comprehensive grasp of our findings and enhance our expertise, we did a meticulous study by meticulously comparing our results with those of previous studies that used the same dataset and followed the same data splitting techniques. The inclusion of a comparative analysis in our research has proven to be highly informative, as it has provided us with valuable context that allows us to assess the significance of our findings in relation to the existing body of knowledge (Table II, and Fig. 9).

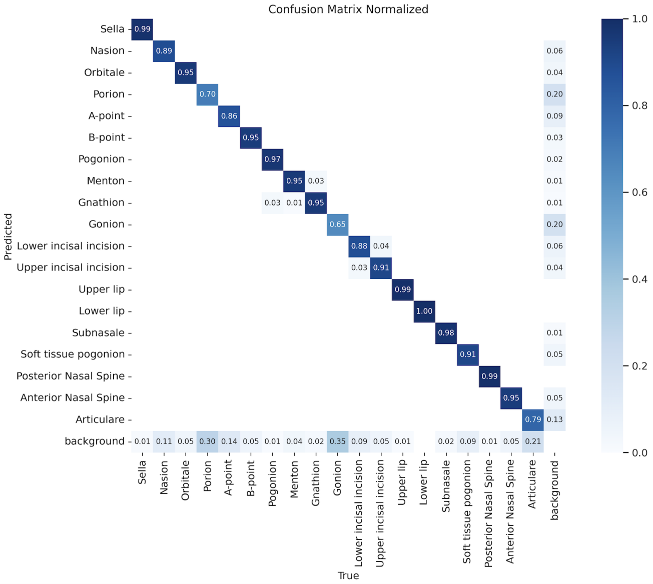

Fig. 6. Normalized confusion matrix for 3mm SDR.

TABLE II. COMPARISON OF RESULTS

	2mm	2.5mm	3mm
Ibragimov et al.[25]	62,74	70,47	76,53
Lindner et al. [26]	66,11	72,00	77,63
Arik et al.[19]	67,68	74,16	79,11
Qian et al. [27]	72,40	76,15	79,65
Oh et al. [28]	75,90	83,40	89,30
CephaX [29]	74,58	83,40	89,30
Our Model	86,31	87,69	90,84

After a thorough presentation of our findings and a meticulous examination of existing literature, our attention now turns towards a deeper exploration and analysis. In the forthcoming section, we embark on a more profound exploration of the complexities inherent in our discoveries. The primary objective of this discussion chapter is to provide a comprehensive context for our findings within the wider realm of established knowledge, elucidating the intricacies and ramifications of our research outcomes.

C. Discussion

The progressive assimilation of deep learning-driven artificial intelligence (AI) algorithms in the realm of medical image analysis has established a paradigm-shifting domain, particularly within the discipline of orthodontics. At the core of this metamorphosis lie cephalometric images, which serve as a crucial diagnostic instrument in assessing the complex interconnections among the mandible, maxilla, dentoalveolar structures, and in identifying dental and skeletal irregularities. The indisputable significance of cephalometric analysis in the field of orthodontics cannot be overstated. Nevertheless, it is imperative to acknowledge that this particular procedure is a complex and laborious undertaking, as its results are prone to fluctuations due to inherent variances in individual anatomical

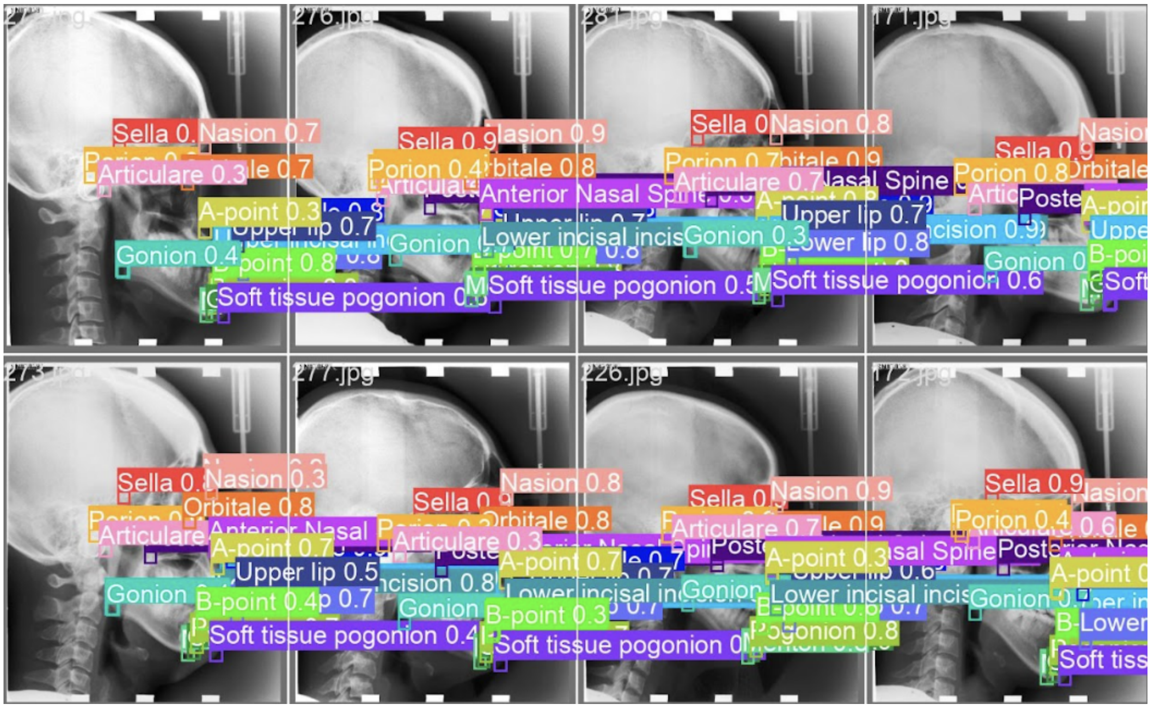

Fig. 7. Predicted batch sample.

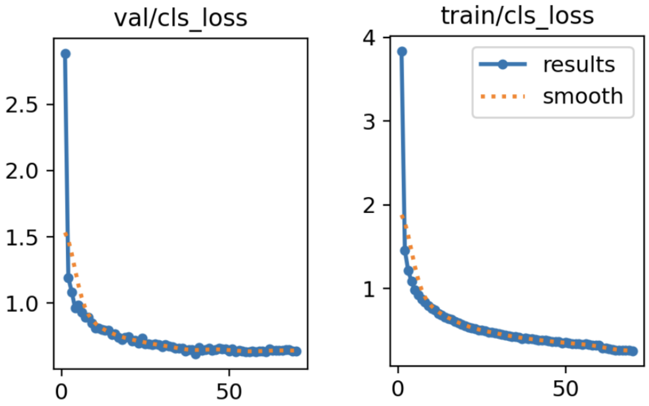

Fig. 8. Loss function.

structures.

The potential impact of AI algorithms in this particular context should not be underestimated. Numerous studies present in current scholarly literature provide substantial evidence supporting the effectiveness of diverse artificial intelligence (AI) techniques in facilitating and optimizing cephalometric analysis. The present study serves to augment the expanding reservoir of knowledge in this field. The YOLOv8 model exhibited varying levels of performance within the specified range of dimensions, specifically 2 mm, 2.5 mm, and 3 mm. Notably, the average SDR scores achieved were 86.31, 87.69, and 90.84, respectively. These results underscore the model's promising capabilities and aptitude in the given context.

Yet, a dive into literature and our observations indicate challenges in the automated detection of certain cephalometric landmarks. Specifically, points like A point, Go, Pg', and Or have traditionally posed challenges, often recording higher error rates or comparatively lower SDR scores. The Soft tissue pogonion point , as alluded to in [28], further exemplifies this challenge.

Notably, the A-point position being susceptible to variations based on head positioning, often complicates its precise tracing. This vulnerability of the A-point, corroborated by prior studies, underscores it as a landmark frequently marred by identification errors [5].

Notwithstanding the valuable insights provided by our research, it is imperative to duly recognize and address the limitations associated with our study. The images utilized in this study were obtained exclusively from a single source, ensuring consistency in terms of exposure parameters.

Furthermore, the labeling of these images was performed by an orthodontist, thereby ensuring accuracy and expertise in the categorization process. Moreover, it should be noted that the lack of external dataset validation and the restricted range of cephalometric landmarks examined could potentially impact the applicability of our results.

The story does not culminate at this juncture, as there exists an additional salient aspect necessitating a comprehensive examination. In the realm of orthodontics, the soft tissue paradigm [30] has ushered in a new era of comprehensive analysis, where the influence of facial soft tissue is taken into account in various jaw and tooth movements. Cephalometric studies encompass a range of soft tissue parameters, including but not limited to facial convexity, nasolabial angle, the positioning of the upper and lower lips, the mentolabial sulcus, as well as the positioning of the soft tissue chin and lower anterior face height [2].

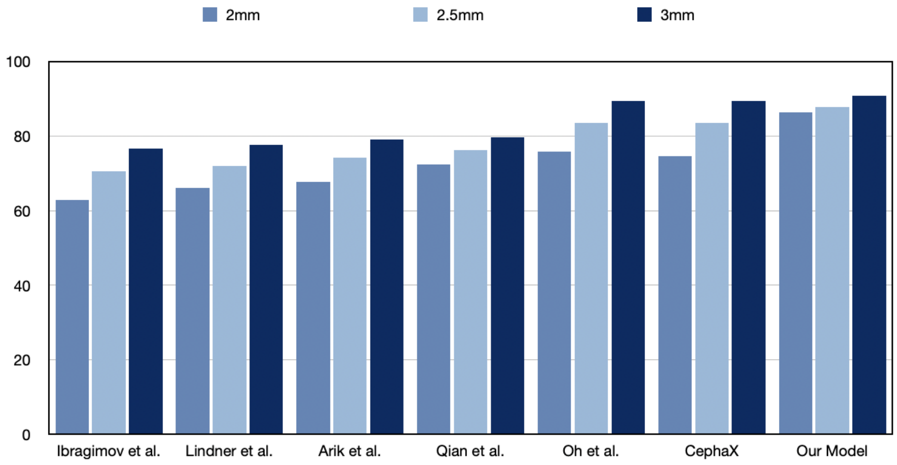

Fig. 9. Comparison of results.

The aforementioned characteristics are crucial in the field of orthodontics for making well-informed decisions on whether to pursue extraction or non-extraction treatment [31]. They play a crucial role in determining the degree of anterior teeth retraction, assessing growth changes, and evaluating surgical movements of the maxilla and mandible. In a recent investigation, it has come to light that the currently accessible datasets for soft tissue cephalometric analyses suffer from a notable limitation. These datasets only provide a small number of four soft tissue landmarks, making them insufficient for undertaking thorough analysis of soft tissue structures.

Soft tissue cephalometric analyses play a crucial role in various fields, including orthodontics, plastic surgery, and facial reconstruction. These analyses involve the examination and measurement of soft tissue landmarks to assess facial proportions, symmetry, and other relevant parameters. However, the limited number of soft tissue landmarks available in publicly accessible datasets severely hampers the accuracy and comprehensiveness of such analyses. The scarcity of soft tissue landmarks in these datasets poses a significant challenge for Furthermore, it is noteworthy that the existing datasets lack crucial occlusal landmarks, which play a pivotal role in the establishment of the occlusal plane. This plane holds significant implications in orthodontic diagnosis and treatment planning, as it has the potential to undergo alterations throughout the course of treatment. Consequently, a pressing demand arises for a novel dataset focused on cephalometric landmark detection. This dataset would efficiently address the current constraints and assist academics in developing sophisticated algorithms that might greatly improve cephalometric decision-making processes.

It is also worth noting that, Cephalometric analysis stands as a cornerstone in both orthodontics and orthopedics, relying on accurately identifying cephalometric landmarks. These landmarks are crucial reference points for a variety of measures and evaluations essential for diagnostic processes [32]. Steiner analysis and Tweed analysis are approaches that use several cephalometric landmarks to assess facial proportions, jaw connections, and dental inclinations. Dr. Tweed's research focused on the prognostic significance of landmark configurations [33]. Cephalometric study is useful not only for assessing dental parameters but also for evaluating upper airway dimensions and potential blockages. Precise recognition of landmarks is essential for assessing parameters like nasopharyngeal airway (NPA) depth and width, soft tissue thickness at various airway levels, and the relationship between the hyoid bone and the mandible, all of which impact airway openness and diagnostic precision.

VI. Conclusion

The integration of deep learning and artificial intelligence (AI) algorithms in medical image analysis, particularly in orthodontics, offers a promising approach to improve diagnostic precision and operational efficiency. The study examining the application of YOLOv8 for cephalometric landmark identification has strengthened the potential of these technical developments. The algorithm exhibited notable levels of accuracy within certain thresholds. However, it still faces persistent challenges, particularly in consistently detecting specific landmarks. Moreover, the variations in experimental procedures and inherent constraints of the study emphasize the need for wider and more varied testing environments.As the interaction between artificial intelligence (AI) and orthodontics becomes increasingly prominent, it is crucial for the technology and clinical sectors to work together to improve the effectiveness and usefulness of these technologies. Research such as ours is crucial in shaping the future of orthodontic diagnostics, which holds the potential for a harmonious integration of human expertise and technical proficiency.

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A Robust License Plate Detection and Recognition Framework for Arabic Plates with Severe Tilt Angles

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***Abstract*—This paper addresses the challenge of accurately detecting and recognizing Arabic license plates, particularly those subjected to severe tilt angles. It presents a robust license plate detection and recognition framework that consists three main steps: plate detection and segmentation, plate perspective correction, and vehicle number recognition. In the first step, a mask R-CNN model is used to detect the plate location, providing pixel-wise labels of identified plates' areas. Following this, a perspective correction technique is used to obtain a clear and rectangular image of each license plate in the image. Lastly, the framework employs a Bidirectional Long Short-Term Memory (Bi-LSTM) model for accurate vehicle number recognition. The framework's efficacy is demonstrated through its application to build a plate recognition system tailored for Egyptian license plates. The system was tested on a dataset collected from campus gate cameras at Zewail city of science and technology, achieving a character accuracy of 97%.**

Keywords*—*License plate detection; license plate recognition; feature extraction; Mask R-CNN; object detection

I. Introduction

The Automatic License Plate Recognition (ALPR) systems have become integral to modern transportation and smart city initiatives [1]. The rapid evolution of surveillance systems has increased the reliance on and demand for ALPR to analyze and process the extensive amounts of camera feeds generated daily. An efficient and reliable ALPR system is critical in many smart city applications including toll collection, safety monitoring, managing border crossings and parking management.

A typical ALPR system consists of three main stages: plate detection, character segmentation, and character recognition [2]. The process begins with plate detection, which locates the plate within the image. This is followed by character segmentation, which isolates each character or digit within the plate. Identified characters are then processed via a character recognition model that reads the plate number.

The incorporation of character segmentation and recognition in ALPR systems faces significant challenges when adapted to new environments [3]. Key challenges include different camera orientations, changes in illumination, and variations in image quality. For instance, models trained on license plates positioned directly in front struggle with footage from cameras mounted at high elevations or at acute angles to moving vehicles, significantly diminishing their recognition accuracy [4].

Furthermore, license plate designs vary across countries, with notable variations in size, language, color, and font. Accordingly, a one-size-fits-all system is impractical and there is a necessity for adaptable frameworks to guide the implementation and customization of these systems across diverse contexts [5].

Several recent research efforts have been proposed to address the above issues. Lin and Li [6] suggest the use of three-stage ALPR system that utilizes YOLOv2 for vehicle localization, in the first stage, and license plate localization, in the second stage. The final stage employs a mask R-CNN to detect each character in the plate. A similar approach is used in [5], where the authors suggest a three-stage system. The first stage employs Faster R-CNN to localize vehicles, followed by the use of morphological operations to localize license plates within the detected vehicles. The final stage utilizes a deep learning model for character recognition. Another approach [7], focused on license plate detection, uses a faster R-CNN for vehicle detection, morphological filtering for license plate detection. These efforts focus on recognition of non-Arabic plates.

Fewer research efforts have focused on Arabic plate recognition [8]. The nature of the Arabic characters, including its right-to-left writing system, complicate segmentation and recognition tasks. Additionally, model performance may be affected by environmental factors such as lighting conditions, plate obfuscation, and the presence of dust or damage on the plates. While using advanced deep learning techniques have shown promise in overcoming these challenges [9], most of the proposed techniques require extensive, diverse training datasets and careful tuning to build robust models. Further research is essential to enhance the robustness of Arabic license plate recognition systems.

This paper presents a robust framework for Arabic license plate detection and recognition. The framework is structured into three key steps. In the first step, the framework employs a Mask R-CNN model [10] for precise localization and segmentation of license plates. This is followed by a technique for perspective correction, ensuring each plate is presented in a clear and standardized rectangular format. Finally, the system incorporates a Bidirectional Long Short-Term Memory (Bi-LSTM) model, specifically employed to achieve accurate recognition of Arabic plate letters and numbers.

The system was trained using two datasets: the first dataset is a synthetic dataset, available on Kaggle [11], which consists of 5k of Arabic license plate images. The second dataset, which includes 2,712 real images from 300 unique cars, was gathered at a toll gate in Egypt. The dataset was originally created by Elnashar et al. [12]. We extended it by adding annotations of the license plate letters and numbers. The efficacy of the recognition was validated using a test dataset of real 140 images collected from cameras at the entrance of Zewail City of Science and Technology. The system achieved a character accuracy of 97%.

II. Related Work

As discussed earlier, the proposed framework has three main stages: license plate detection, perspective correction, and license plate recognition. This section reviews some prominent research efforts in license plate detection and recognition. In our review, we focus on Arabic license plate detection and recognition, as this is the scope of this work.

A. License Plate Detection

Traditional license plate detection methods have utilized image processing techniques, such as the Sobel edge detector [13] and the Hough transformation [14], to detect lines and edges in the given image, providing a way of identifying the license plate's boundaries. These methods, however, are prone to errors from noisy edges and complex images.

Plate texture is also used as a good detection indicator of the plate. Techniques such as Gabor filter [15] and Wavelet transform [16] have been used to detect the plate using its texture. Others used a decision tree with adaptive boosting on Haar-like characteristics [17]. This algorithm performed well in multiple camera orientations and lighting conditions. It achieved an accuracy of 94.5%.

Recently, deep learning techniques have been used extensively in license plate detection mechanisms. For instance, YOLOv3 was used to detect plates on multi-style Egyptian license plates [12]. This approach achieved 99.2% plated detection accuracy on the new standardized Egyptian license plates and 96.8% for the older versions of Egyptian plates. Another example is the detection algorithm in [18]. The algorithm uses a region-based convolutional neural network (R-CNN) to achieve dual objectives: plate detection and estimation of the four corners of the plates. Subsequently, the identified points were utilized to perform an affine transformation on the plates, correcting any tilt angles present.

B. License Plate Recognition

Automatic Arabic License Plate Recognition (AALPR) systems can be classified into two main approaches: segmentation-based approach [19] and segmentation-free approach [19] & [20]. The segmentation-based approach segments individual license plate characters and then detects each character using an OCR model. Elsaid, et al. [21] proposed a segmentation-based approach trained on Arabic and Indian numerals and Arabic alphabets on Saudi Arabian license plates. The proposed pipeline has five stages: license plate preprocessing, license plate localization, character segmentation, features extraction, and character recognition. It was tested on 470 license plates with different effects such as skewness and noise, achieving 96% segmentation accuracy and 94.7% recognition rate.

Antar et al. [22] proposed a method for detecting and recognizing vehicle license plates. A canny edge detector is used for the detection module, combined with other noise reduction techniques. The recognition module uses a masking technique to locate regions of interest in the license plate and applies a character recognition model to classify each region. The model achieved 96% accuracy for English and 92.4% accuracy for Arabic. Sarfraz et al. [13] performed character segmentation and normalization, then template matching with Arabic characters.

Shehata et al. [19] proposed four systems to recognize license plates. The first system is a segmentation-based approach and has three main modules: license plate extraction, character segmentation module, and character recognition module. The character recognition component employs a KNN classifier to assess the resemblance between the segmented characters and the reference characters stored as ground truth. The second system has the same modules as the first system but uses Deep CNN for feature extraction and Deep CNN for character recognition. The system was tested on 300 license plates and got 0.95 recall, 0.95 precision, and a character recognition accuracy of 0.99 which lead to license plate accuracy rate of 0.95.

The third system in Shehata et al.'s work is a segmentation-free approach. The model is based on two classical machine learning modules: license plate feature extraction and license plate recognition. The system was tested on 100 license plates and got 0.76 recall, 0.85 precision, and accuracy rate of 0.90. The fourth system is another free-segmentation approach with two deep learning modules: plate detection and plate recognition. The system was tested on 1000 license plates and got 0.89 recall, 0.91 precision, and accuracy rate of 0.93.

III. The License Plate Detection and Recognition Framework

As discussed earlier, the framework has three main stages: the plate detection and segmentation step, plate perspective correction, and plate recognition. A system implementing the proposed framework is shown in Fig. 1. The proposed system has four main components: the segmentation model, the corner estimation, the plate warping model, and the plate recognition model.

The first stage of the framework, plate detection and segmentation, is implemented via the license plate segmentation model shown in Fig. 1. The output of this model is pixel-wise segmentation of the detected plate, as indicated in the Figure. It should be noted that the model is trained to detect the plate directly without detecting the vehicle first.

The second stage, plate perspective correction, is implemented via the corner estimation and plate warping components. The segmented plate is passed through a series of operations to estimate the corner of the plate's rectangular area, namely edge detection, contour fitting, and contour fine-tuning. A homography transformation is then calculated and applied in the plate warping component to correct the plate perspective.

The corrected plate is passed to the recognition module in the last stage to get the recognized characters. The details

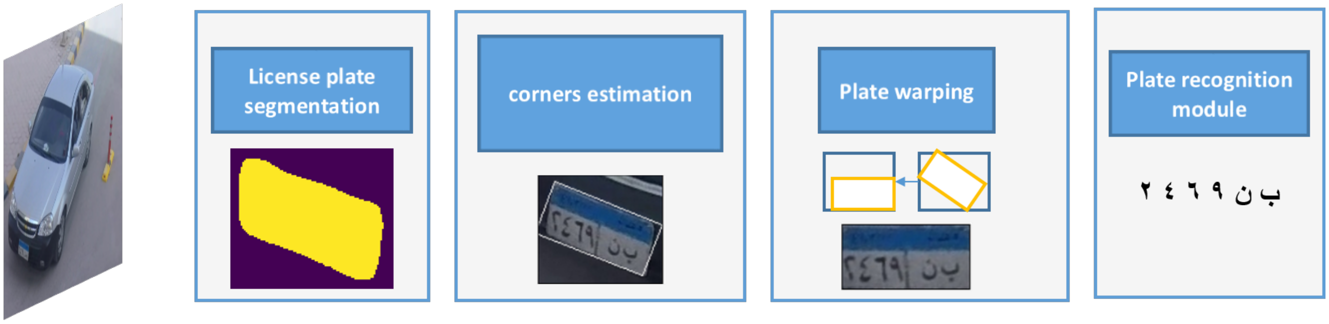


Fig. 1. System overview.

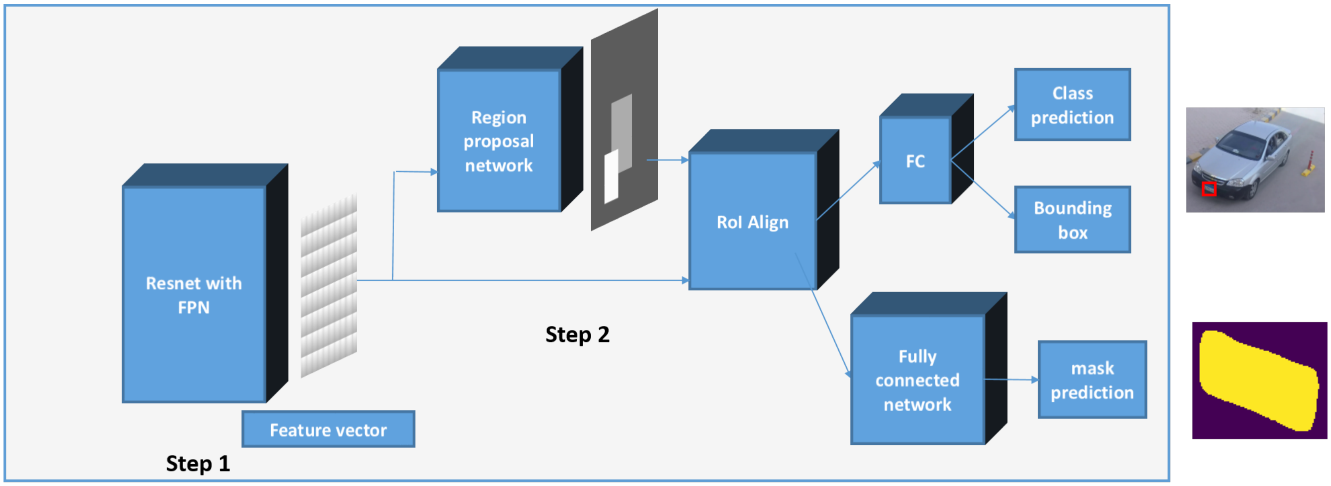


Fig. 2. Mask R-CNN.

about each model are discussed in the following subsections.

A. Plate Detection and Segmentation

We used Mask R-CNN [10] to detect the plate and its bounding box. Mask R-CNN is an extension for faster R-CNN [23] where a fully connected head is added to the faster R-CNN network to get additional output for the bounding boxes and classes. It gives a pixel-wise annotation for the image, which offers highly accurate labels. The segmentation enables us to get arbitrary shapes that describe precisely objects of interest. Mask R-CNN is shown in detail in Fig. 2.

Faster R-CNN is composed of two main parts. The first part proposes potential object bounding boxes using a region proposal network (RPN). In the second part, a region-of-interest (RoI) Pool layer extracts features for each potential bounding box, classifies it, and regresses its bounding box.

Feature extraction is done using ResNet [24] and Feature pyramid network (FPN) [25]. Features from ResNet are passed to RPN, which uses a sliding window to perform convolutions on different positions of the image using multiple anchors to detect the license plates. FPN passes different scales of the input image to the RPN. Using different scales of the input image makes the network more robust at detecting small license plates.

Mask R-CNN has the same structure as faster R-CNN, with the first part being the same (RPN). However, in the second part, a binary mask is formed parallel to class and bounding box predictions. This parallel computing simplified the training process greatly by combining multi-task loss and optimizing them concurrently on each potential object of interest. Multi-task loss is formed as shown in Eq. (1)

$$L = L_{cls} + L_{box} + L_{mask} \tag{1}$$

where L_{cls} & L_{box} are the classification and bounding-box loss, respectively, as defined in faster R-CNN. The mask network has dimensions of m^2 for each potential object of interest. For each pixel, a sigmoid activation function is computed. L_{mask} is computed by taking the mean of the cross entropy loss over all the pixels.

B. Corner Estimation

After the plate segmentation extraction step, we process the image to estimate the corners of the segmented plate image to be used in correcting the plate perspective as shown in Fig. 3. First, we apply edge detection to help get the minimum rotated bounding box. Then, we use a canny algorithm [26], which passes the images through multiple steps to find the edges.

To get the rotated bounding box coordinates, we use a rotating calipers algorithm [27] to find the minimum bounding box that fits the segmentation polygon output. The rotated

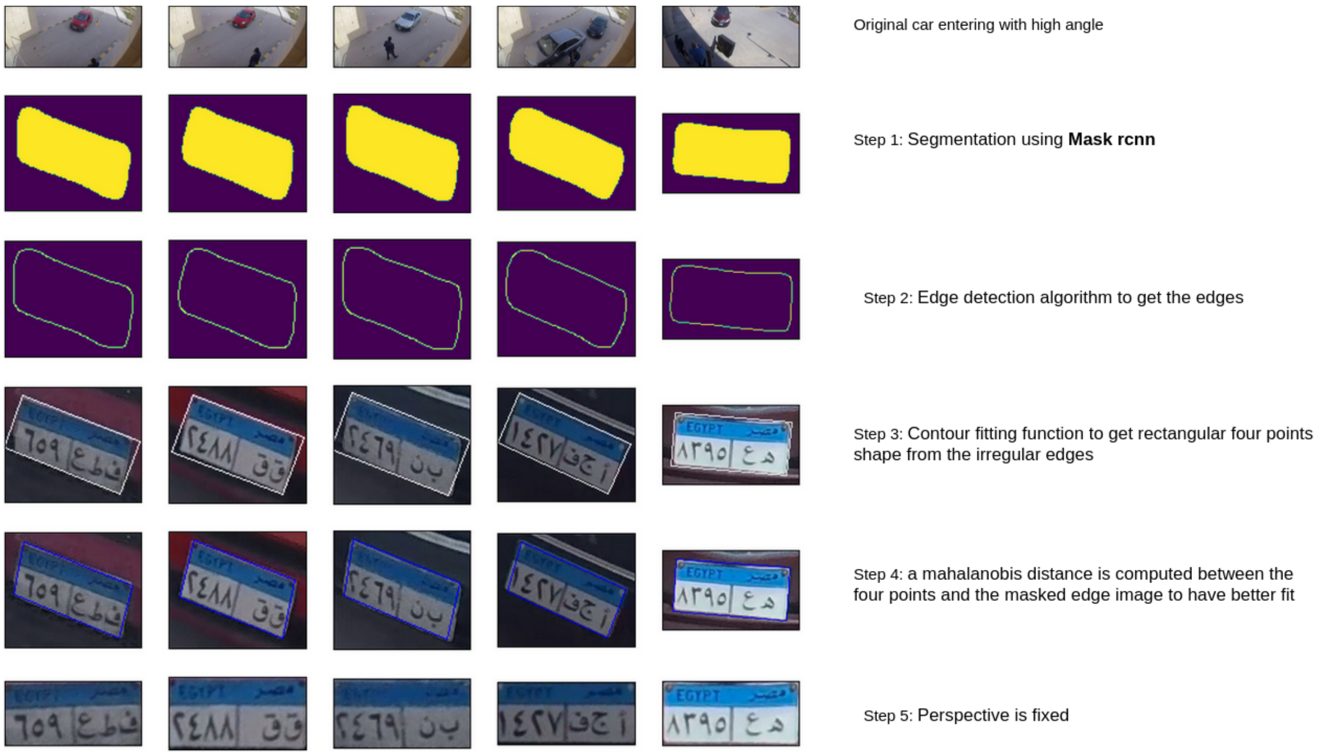

Original car entering with high angle
Step 1: Segmentation using **Mask rcnn**
Step 2: Edge detection algorithm to get the edges
Step 3: Contour fitting function to get rectangular four points shape from the irregular edges
Step 4: a mahalanobis distance is computed between the four points and the masked edge image to have better fit
Step 5: Perspective is fixed

Fig. 3. Perspective correction steps.

caliper algorithm starts with fitting a rectangle having one side aligned with the target polygon and a set of the polygon vertices. It updates the coincident edge and the vertices until it reaches the minimum fitting rotated bounding box efficiently in just O(n), where n is the number of polygon vertices.

C. Plate Warping

Due to the tilted angle of the camera, the detected plates do not have a rectangular shape, which affects the character recognition task. In this step, we fix the plate's perspective projection, improving the plate character recognition accuracy. The perspective transformation changes the viewpoint of the image, e.g., the angle, lengths, and geometry of the lines, but it keeps the collinearity of the points. Hence, we can correct the perspective of the plate by computing the transformation matrix needed to translate points from their actual view to the front-facing view. The transformation uses the actual viewpoints and the targeted points to get the matrix. This operation can be formulated using the transformation matrix in Eq. (2)

$$\begin{bmatrix} x^{'} \\ y^{'} \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & e \\ c & d & f \\ g & h & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{2}$$

where constants a,b,c,d control rotation and scaling transformation, e,f control the translation vector, and g,h are the projection vectors.

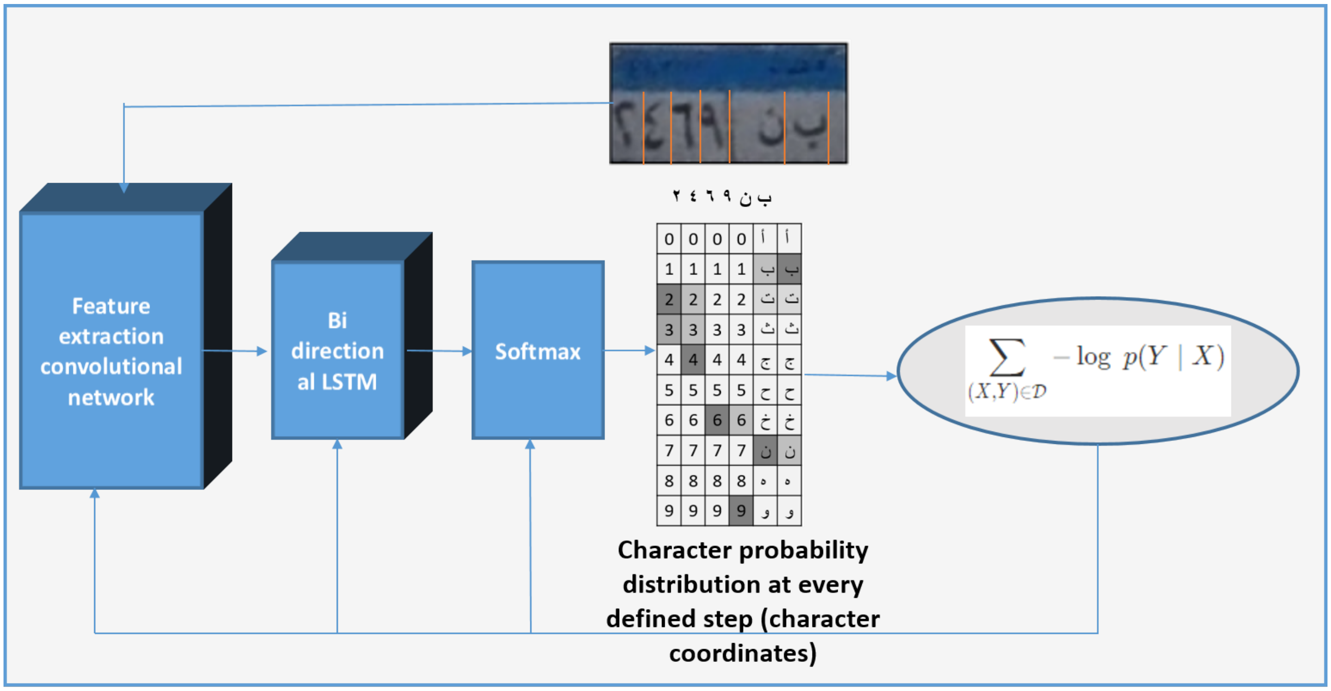
We use the four input points (estimated corners) and their targeted location points (rectangular shape) to have eight equations that could be solved simultaneously to get the transformation constants.

D. Plate Character Recognition

Because of its excellent performance in different detection and recognition vision tasks, we initially trained and tested the YOLOv5 model for character recognition. However, the results could have been better after fine-tuning the model, as discussed in the experimental results section. Thus, we developed a new model for character recognition. The plate character recognition proposed module has two main steps: license plate feature extraction and character predictions. We will show the components of each module and how they are combined and trained at once to best solve the problem of limited datasets. We use a stack of CNN and RNN layers so that it can perform character-level inferences without the need for an explicit step for character segmentation.

License plate features extraction: Inspired by the VGG network [28], a CNN is used for character feature extraction. The ReLU activation function is used after each convolutional layer to add nonlinearity to the network. We used batch normalization for regularization. He initialization [29] was used to prevent the vanishing gradient problem and speed up the training process. The channel information was gradually reduced after each CNN layer using the maxPool layer to the required timesteps. Afterward, the feature extraction output is passed to the RNN layers using the Bi-directional LSTM.

Characters prediction: The developed model uses RNN to learn the sequential relations found in the license plates


ب ن ٩ ٦ ٤ ٢
Feature extraction convolutional network
Bi direction al LSTM
Softmax
$\sum_{(X,Y)\in\mathcal{D}} -\log\ p(Y \mid X)$
Character probability distribution at every defined step (character coordinates)

0	0	0	0	أ	أ
1	1	1	1	ب	ب
2	2	2	2	ت	ت
3	3	3	3	ث	ث
4	4	4	4	ج	ج
5	5	5	5	ح	ح
6	6	6	6	خ	خ
7	7	7	7	ن	ن
8	8	8	8	ه	ه
9	9	9	9	و	و

Fig. 4. Plate recognition module.

combined with the CTC loss presented in Eq. (3).

$$\mathcal{L}_{CTC} = -\log p(\mathbf{y}|\mathbf{x}) = -\sum_{\mathbf{s}\in\mathcal{B}(\mathbf{y})} \log p(\mathbf{s}|\mathbf{x}) \tag{3}$$

where

- $\mathbf{y}$ is the target sequence, which is the ground truth license plate characters.
- $\mathcal{B}(\mathbf{y})$ is the set of all possible label sequences that can be derived. It includes all possible combinations of the target sequence with additional blank labels inserted between and after the characters, representing all possible alignments of the characters in the input sequence.
- $p(\mathbf{s}|\mathbf{x})$ is the probability of label sequence $\mathbf{s}$ given the input sequence $\mathbf{x}$, as computed by the CTC model. This probability is estimated by the neural network during training.
  The loss is computed as the negative log-likelihood of the target sequence, given the input sequence and the probabilities of all possible label sequences.

The whole network of the CNN and RNN is trained end to end using CTC loss. This takes care of extracting the implicit rules that are present in the license plates. For instance, the Egyptian license plate uses a structure in which, if the plate is read from left to right, the plate has four digits followed by three characters. By learning the sequence, the network can predict getting a digit in the first four values and characters in the last three.

Those learned rules direct the training of the feature extraction in the CNN layer. The whole network parameters are trained and optimized at once from the CTC loss. The loss is between labels, and targets are backpropagated to update all the parameters. Finally, a dense layer maps the output of the RNN network to the predicted category. We use the SoftMax function to obtain the probability of the correct character as shown in Fig. 4

The CTC loss function is used to decode sequential information to align plate characters in a segmentation-free way. This approach also has the advantage of not needing bounding box annotation for every character, simplifying the learning process. An annotator only needs to record the character of every license plate on a sheet.

CTC technique allows the training of sequence-to-sequence models, such as recurrent neural networks (RNNs), with variable-length inputs and outputs. It works by defining a set of possible alignments between the input and output sequences, called the “blank label” set, and computing the likelihood of each alignment given the input sequence.

In terms of time steps, CTC works as follows:

1) At each timestep, the RNN generates a probability distribution over all possible labels, including a special “blank” label.
2) For each possible label sequence, the CTC algorithm computes the probability of that sequence given the input sequence.
3) The CTC algorithm then sums the probabilities of all possible label sequences that can be derived from the target sequence by inserting, deleting, or repeating the blank label.
4) The CTC loss function is defined as the negative log-likelihood of the target sequence given the input sequence and the probabilities of all possible label sequences.

5) During training, the RNN's parameters are updated to minimize the CTC loss.
6) In the decoding stage, the probabilities generated by the RNN are used to find the most likely label sequence. In summary, CTC works by defining a set of possible alignments between the input and output sequences, computing the likelihood of each alignment given the input sequence and minimizing the negative log-likelihood of the target sequence.

The training dataset is fed to the model with a batch size of 256 images. We used the Adam optimizer for faster convergence and better performance using gradient descent and momentum optimization.

IV. Experimental Result

This section discusses the experimental results, starting with a description of the datasets used in the training and testing of the developed models.

A. Datasets

Accurate datasets are necessary for training ALPR deep learning models. There are different aspects to be considered in the ALPR datasets, including environment-related aspects such as illuminations and background; camera point-of-view-related aspects such as the pose of the camera (frontal or upper view), rotation and skew Coefficients; and plate-related aspects such as color distribution, location of the plate with respect to the car, language and font styles.

Multiple datasets have been used in this research to improve the system's overall accuracy. These datasets are 1) the Macathon competition dataset on kaggle [11], 2) the toll dataset [12] and 3) a proprietary dataset collected from CCTV cameras on campus. Table I summarizes the distributions of each dataset.

TABLE I. Datasets Summary

	Datasets		
	Synthetic	Toll	University
Year	2022	2022	2022
number of images	7k	2k	140
LP size	376 x 172	68 x 32	100 x 50
LP angle	Frontal	frontal	Oblique

1) Kaggle macathon competition dataset: The Machathon competition dataset comprises synthetically modified 5k images of Arabic license plates. This dataset has annotations for the plate's characters, including characters' bounding boxes. The images are generated with a high resolution that isn't realistic in real-life scenarios. Samples of the dataset are shown in Fig. 5, and the distribution of the characters is shown in Fig. 6. The distribution indicates that the classes are unbalanced and digits are more common than letters.

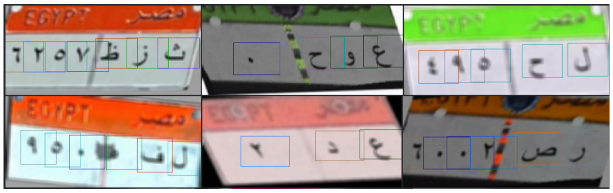


Fig. 5. Macathon competition dataset samples.

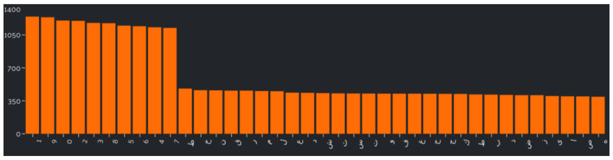


Fig. 6. Macathon competition dataset character distribution.

After inspection of the character bounding boxes, it was noticed that some bounding boxes may cover more than one character, which causes problems if used without correction. As such, we used a bounding box correction process, summarized visually in Fig. 7, to improve the dataset's quality. First, each bounding box is extracted from the image. A fixed constant, decided experimentally, is removed from each margin so the bounding box encloses only one character. Secondly, a K-means segmentation is used to extract three clusters in each bounding box. The bounding box around the largest cluster is considered the corrected bounding box. Finally, annotations are fixed manually to account for errors that could occur due to noise. Samples of the corrected annotations are shown in Fig. 8.

2) Toll dataset: The toll dataset [12], includes real images collected at a toll gate in Egypt. Fig. 9 displays samples from the toll dataset. An imbalance is observed in the toll dataset, as demonstrated in the character distribution in Fig. 10.

The car images are taken from a frontal view camera facing the entering cars, which means the dataset does not present the tilted angle challenge addressed in this paper. The dataset contains 2712 images, corresponding to 300 unique cars, with the license plate at varying proximities from the camera and in different qualities. For the purpose of character recognition, all images were manually labeled with the correct characters and digits shown on the license plate.

3) The Arabic License Plate Recognition (ALPR) Dataset: The Arabic License Plate Recognition (ALPR) dataset consists of two hours of videos captured from two gate cameras at the entry and exit gates of campus. This dataset consists of 140 images that the model has not seen. Samples of this dataset are shown in Fig. 11. As seen in the figure, the dataset is challenging. Due to the pose and height of the camera, all plates are tilted. Some plates have different illuminations, and others are distorted.

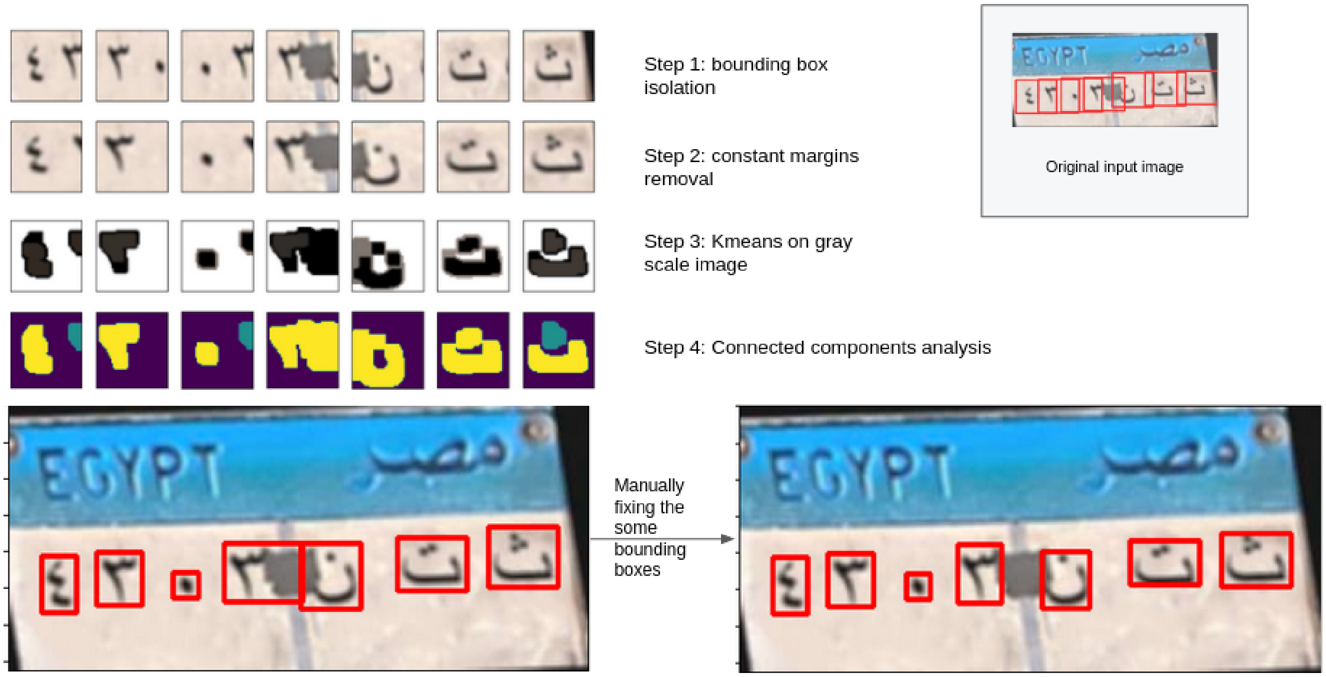

Step 1: bounding box isolation
Step 2: constant margins removal
Step 3: Kmeans on gray scale image
Step 4: Connected components analysis
Original input image
Manually fixing the some bounding boxes

Fig. 7. Synthetic dataset correction steps.

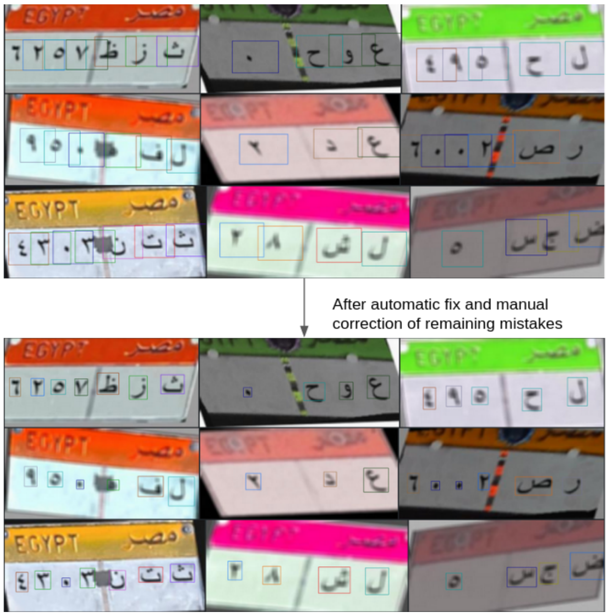

After automatic fix and manual correction of remaining mistakes

Fig. 8. Synthetic dataset before and after corrections.

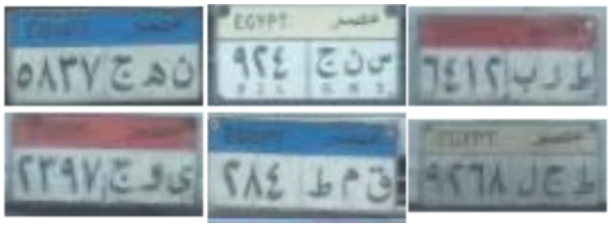


Fig. 9. Sample of the toll dataset.

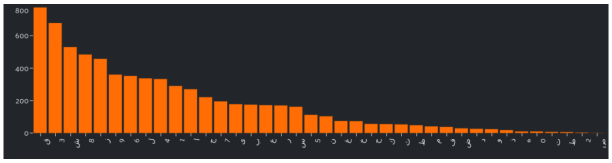
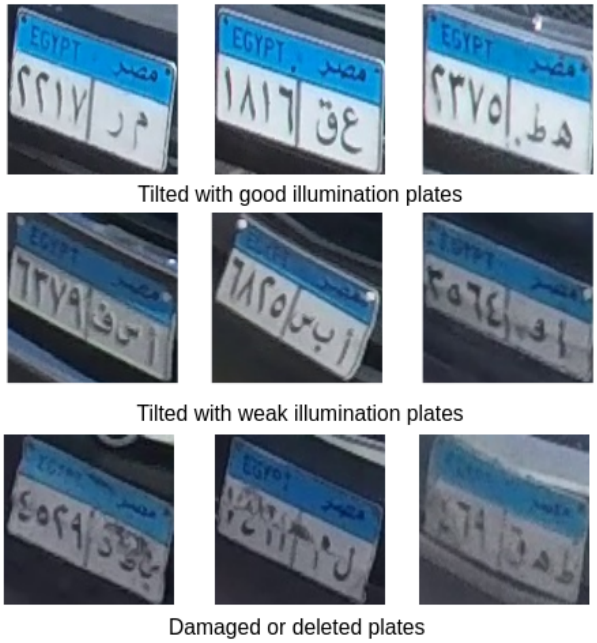


Fig. 10. Toll dataset character distribution.

To enrich the dataset for the character recognition task, an augmentation process was used to increase the dataset 10 times. Plate images were resized to dimensions of 32 pixels in height and 128 pixels in width. Experiments were conducted with different kinds of augmentations, such as random brightness, contrast, image quality, and saturation. Additionally, the recommended YOLOv5 augmentations were used, which include HSV color space augmentation, Letterbox, Mixup, and Random perspective.

B. Results

The plate recognition mechanism was trained on the Kaggle Machathon competition dataset. The dataset was split into three sets for training, validation, and testing. The training dataset was used to extract the patterns of the letters. The validation dataset was used to choose the right parameters of the neural network. Finally, the testing dataset was used to provide unbiased accuracy results. The recognition is tested using two models YOLOv5 and the VGG network supported



Tilted with good illumination plates

Tilted with weak illumination plates

Damaged or deleted plates

Fig. 11. Samples of the ALPR testing dataset and its challenges.

by bidirectional LSTM layers. Table II shows the results when these models were applied to the validation dataset.

Three metrics are used to evaluate the plate recognition model:

1) character accuracy: This metric represents how many characters were recalled correctly
2) Identical 0: This metric represents how many plates were identified completely correctly
3) Identical 1: This metric represents how many plates were identified with a one-character error

TABLE II. Character Recognition Accuracy for the Validation Dataset

Model	Character Accuracy	I0	I0+I1
Yolov5	96.89%	86.43%	98.12%
VGG11 - BI LSTM	99.54%	97.9%	100%

Then, both models were tested on the Campus dataset. Table III shows the accuracy of both models.

TABLE III. Character Recognition Accuracy for the Testing Dataset from the Campus

Model	Character Accuracy	I0	I0+I1
VGG11 - BI LSTM using CTC loss	82.29%	27.9%	67.9%
VGG11 - BI LSTM more training data	94%	73.5%	92.1%
VGG11 - BI LSTM fine-tuned on annotated toll dataset	97%	86%	96.4%

As seen from the table, VGG using bidirectional LSTM surpasses YOLOv5. The list below discusses the performance of the two models.

1) VGG was more accurate than YOLOv5 in mapping the relationship between letters.
   a) There is some correlation between two letters that should appear together in a certain province or area
   b) There is some correlation between letters and digits, meaning that if two or a maximum of three letters appear, the coming characters are sure to be digits. VGG can map this very well, while YOLOv5 makes mistakes in this. For example, the number 4 in Arabic may be misrecognized by letter ع .
2) YOLOv5 requires a lot of data to generalize well on unseen data
3) These results are satisfactory considering the limited availability of training data. The accuracy is expected to increase as the model works and collects more data. For the time being, accuracy can be improved by using a voting mechanism for the recognition results of several images of the same plate. Three stages were shown in training VGG network; the last stage with most data showed the best results on the test set.

Fig. 12 shows a sample of the mistakes encountered when using YOLOv5 but were correctly handled by the VGG. In this case, the number 4 is misrecognized by غ or ع. Fig. 13 shows two plates that were recognized entirely by VGG, but only two letters were recognized when using YOLOv5.

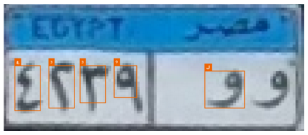


Fig. 12. Some samples not detected by YOLOv5 but were correctly detected by VGG.

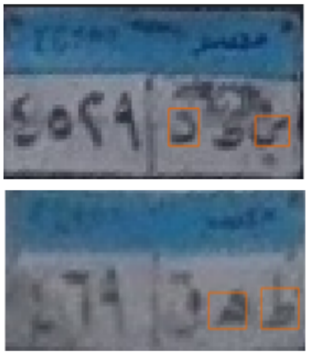


Fig. 13. Challenging samples that were correctly recognized by VGG but not YOLOv5.
Bounding boxes represents the detection of YOLOv5.

V. Conclusion

This study has demonstrated that algorithms with inherent automatic rules extraction, combined with effective preprocessing, outperform deep learning methods for license plate recognition when working with limitations in both the number of instances and the size of images. The results indicate the importance of preprocessing and the potential of automatic context-understanding approaches in applications where data are limited or expensive to obtain. By continuing to refine the methodology and expand the dataset, the aim is to further improve the accuracy and efficiency of license plate recognition systems.

VI. Future Work

In future work, the plan is to further enhance the license plate recognition system by increasing the dataset size, which is expected to improve the model's performance. Additionally, integrating an annotation tool into the system will facilitate the creation and management of annotated data, streamlining the training process for the models. These improvements will help better understand the impact of larger datasets and more sophisticated preprocessing techniques on license plate recognition accuracy. It will also provide the ability to train more deep models that can ingest large datasets.

VII. Acknowledgment

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Future Iris Imaging with Advanced Fuzzified Histogram Equalization

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***Abstract*—Images captured under low lighting frequently exhibit low brightness, low contrast, and a small grayscale. These features can affect the individual's view and severely limit the performance of machine vision systems, particularly when data annotation is involved. Hence, the issues motivate this study to examine the effectiveness of advanced fuzzified histogram equalization for image enhancement. A comparative study was conducted based on the low lighting condition of iris images to evaluate three image enhancement methods: Advanced Fuzzified Histogram Equalization (AFHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), and Fuzzy Contrast Enhancement (FCE) using the MIREIS dataset. The Gaussian membership functions (GMF) were modified accordingly to satisfy the suitable pixel intensity of the input iris images. The results were compared using the peak signal-to-noise ratio (PSNR) value, including the central processing unit (CPU) times. As a result, the AFHE showed a better PSNR value at 76.02db with faster CPU times at 4.04s compared to CLAHE and FCE. Although the PSNR value of HE is slightly lower than CLAHE (0.3%) and FCE (0.7%), AFHE improved the image's quality and brightness, which can help other researchers with the data annotation process. The performance of the proposed methods was validated by comparing them with state-of-the-art methods. The results demonstrated that AFHE, CLAHE, and FCE exceeded other HE, AHE, CLAHE, and hybrid HE using fuzzy approaches that employed PSNR metrics.**

***Keywords*—Image enhancement; fuzzy logic; histogram equalization; CLAHE; iris recognition**

I. Introduction

The quality of the images significantly influences the effectiveness of an iris recognition system. As such, it is crucial to enhance the image quality, especially when dealing with images captured in non-cooperative environments. The non-cooperative environment images provide low-quality data due to the rigidity condition during data acquisition [1]. The near-infrared illumination needed for iris recognition systems that allow for user identification additionally involves the users' cooperation to obtain a good-quality iris image, as these devices are not user-friendly [2]. These requirements impose an extra responsibility on the user to actively engage in the recognition process.

Current studies focus on detecting the iris when an iris image is acquired under varying lighting conditions and at a long distance. Poor quality images, mainly low lighting, reflection, occlusion, off-angle, and motion blur can further decrease iris pattern performance [3]. Nevertheless, when the distance between the iris and the device increases, the quality of the iris image decreases, and more illumination is necessary. Employing a visible light camera does not necessitate further illumination because the captured images present color data [4]. Iris recognition functionality can be integrated into an existing device or reduced to comply with these features.

A study has been conducted using a database comprising iris images captured at 4 to 8 meters with a high-resolution visible camera. The database includes low lighting, rotation, motion blur, and off-angle [5]. Another database contains an iris with face images captured with a visible light camera integrated into mobile devices [6]. The following processes must be followed to improve the quality of iris images: acquisition, enhancement, segmentation, feature extraction, and recognition. Image enhancement refers to converting the image intensity to create a new image and enhance the image quality. The key objectives of image enhancement are improving contrast, adjusting brightness, sharpening, color restoration, and noise reduction.

Various studies have proposed new enhancement methods based on histogram equalization (HE) [7], [8], [9], [10], [11]. By increasing the image's contrast through histogram stretching, HE can enhance the image's visual appeal [12]. The gray grouping approach underpins histogram stretching, which can be utilized for low-contrast and brightness images. It offers several benefits, including the fact that it is both simple and highly effective. While iris image enhancement technologies are generally efficient [13], they can lead to over-enhancing of the image if there is a prominent peak in the histogram [14]. In addition, HE tends to adjust the image's average brightness to the dynamic range's midpoint. This limitation renders the HE impractical in multiple technological applications.

This study is motivated by the crucial need for high-quality images in iris recognition systems, especially in challenging environments where image quality can be affected by factors like low lighting, reflections, occlusion, off-angle capture, and motion blur. Current methods frequently encounter challenges in retaining performance in these conditions, requiring the development of image enhancement methods to tackle these issues. While previous studies have investigated image enhancement methods such as HE, limitations such as over-enhancement and impractical brightness adjustments emphasize further investigation into more effective image enhancement methods for iris recognition systems.

The paper is structured as follows: Section II discusses the state-of-the-art image enhancement for iris recognition, and Section III presents a comprehensive explanation of the fuzzification process of advanced fuzzified histogram equalization (AFHE), contrast limited adaptive histogram equalization (CLAHE), and Fuzzy contrast enhancement (FCE). Section IV provides the experimental data and analysis, while Section V concludes this paper.

II. Related Works

Previous studies on iris image enhancement used images acquired from low lighting and NIR illumination to tackle image over-enhancing and brightness problems. A study in [12] employed HE to improve the visibility of iris images captured under low lighting conditions, aiming to determine the borders of the pupil area. This approach accomplished redistributing pixel intensities. Hence, the darkly pigmented iris reduced the HE outcome due to the low contrast ratio between the iris and pupil.

Maheshan et al. [15] employed HE and CLAHE methods for analyzing fuzzy sclera. In this study, HE aims to find the frequency of dark colors, which typically covers a range of zero to fifty pixels. Conversely, the CLAHE establishes a limit on contrast that provides a proportional adjustment of white balance for the image. Hassan et al. [1] conducted a comprehensive study on HE, CLAHE, and HE for iris images at varied distances and in visible wavelength illuminations. The study aims to improve iris segmentation and recognition performances.

A study in [16] introduced the CLAHE approach to enhance the performance of iris recognition in low contrast or low illumination conditions. It is an improved version of the adaptive histogram equalization (AHE) method initially developed by Zuiderveld [17]. This technique reduces potential noises in the image while enhancing contrast in grayscale images. A study in [18] presented an image enhancement method using HE to increase the quality of iris images for rubeosis iridis disease. The processes were divided into three image groups: low, medium, and high. The best results for the low contrast group enhanced by 50%; however, it can be reduced by 50% in the high contrast group.

An advanced recognition system in [19] proposed a Convolutional Neural Network (CNN) with HE and CLAHE to efficiently enhance and detect COVID-19 diseases in chest X-ray images. AlKhalid in [20] proposed the same model; CNN combined with HE and CLAHE using COVID-19 chest X-ray images for data expansion, transformation, and enhancement. Two layers of HE are applied to seven layers of data transformation; however, the study begins with a conceptual hashing algorithm to eliminate duplicate images. A study in [21] introduced CNN with HE and CLAHE to produce high-contrast tooth X-ray images. The proposed method created high-intensity data to visualize the tooth features, including the infection, inflammation, and nerve.

In study [22], Xiong et al. proposed a chaotic Pareto sparrow search algorithm (CPSSA) with CLAHE for iris augmentation. The CPSSA algorithm utilizes population-based iteration to search for specific clipping thresholds that meet the specified criteria, resulting in CLAHE generating a collection of iris images. A study in [23] applied HE and AHE to compare with Canny edge detection. The AHE aims to determine the iris patterns with high-contrast images. The Canny edge detection combined with HE produced a sharper, more structured image with less noise. On the other hand, the Canny edge detection method with AHE introduced more noise in the final images. However, these images exhibit more robust features than those obtained using conventional HE.

The enhancement method proposed by Chang et al. [24] eliminates the specular reflections from the iris image by applying the preprocessing method to the input image in three stages. The initial phase was applying the Gaussian filter method with a sigma value of 0.9. The second stage involved converting the ocular images from grayscale to binary using a threshold value of 0.18. Finally, the binary iris image was exposed to a Gaussian filter with a sigma value of 2, followed by a median filter to enhance the image's smoothness.

A study in [25] utilized fuzzy membership weighted functions to analyze image pixel values. With a triangle function, the fuzzy average and fuzzy median filters outperform the other four fuzzy filters in terms of filtering performance. Without using deep learning, these fuzzy techniques were employed to improve images. For instance, a one-pixel attack on an image can significantly change the prediction's outcome [26]. The resilience of neural networks can be enhanced by utilizing the fuzzified image enhancement in deep learning.

Orujov et al. [27] developed a contour detection algorithm using Mamdani (Type-2) fuzzy rules for blood vessel detection in retinal fundus images. It utilizes green channel data, Contrast-Limited Adaptive Histogram Equalization (CLAHE), and a median filter for background exclusion. The method achieved accuracies of 0.865, 0.939, and 0.950 on STARE, DRIVE, and ChaseDB datasets, respectively, demonstrating flexibility and comparable performance to existing methods, with potential for dynamic rule formulation in image processing systems.

Another study in [28] applied fuzzy average, fuzzy median, and Gaussian filters to preprocess iris images that had reflections on glasses and were occluded by eyelids and eyelashes. This preprocessing aimed to improve the out-of-bounds areas, enhance the noise ratios, and sharpen the edges of the iris images. However, the success rate remained poor, prompting the employment of morphological operations and other alternative preprocessing approaches.

This study proposed advanced fuzzified histogram equalization (AFHE) based on the modified Gaussian member functions to enhance the quality of low-lighting iris images, facilitating the data annotation process. The quality assessment of low-lighting iris images is evaluated based on the Peak Signal-to-Noise Ratio (PSNR) while optimizing the central processing unit (CPU) time. The proposed methods were compared with state-of-the-art methods to benchmark and validate the performance.

III. Materials and Method

This section discusses the materials used to implement the image enhancement methods. Fig. 1 illustrates the enhancement process that begins with data collection for iris images. The original image retains its dimensions without performing image resizing. The iris images are subjected to the image enhancement methods AFHE, CLAHE, and FCE, with equal distribution of intensities. Finally, the iris images are trained to achieve the PSNR values based on the implemented methods.

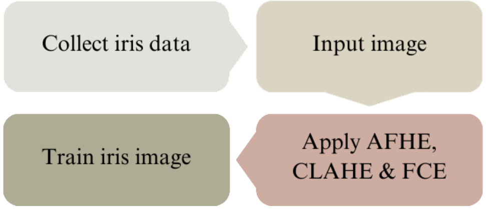

Fig. 1. Image enhancement system flow for AFHE, CLAHE, and FCE.

A. Dataset

This study employs 24 iris images from the Mobile Iris-Eye Computer Vision (MIREIS) dataset to test the image enhancement techniques for low lighting conditions as presented in Fig. 2. The iris images were captured using an iPhone 13 in early 2023 at the Universiti Teknologi Malaysia, Kuala Lumpur. The dataset focuses on the iris occlusions, motion blur, reflection, visible illuminations, and low-lighting conditions. Therefore, it is available for only several images in low-lighting conditions. The iris images are in standard exposure and RGB color space with the dimension of 2316 × 3088.

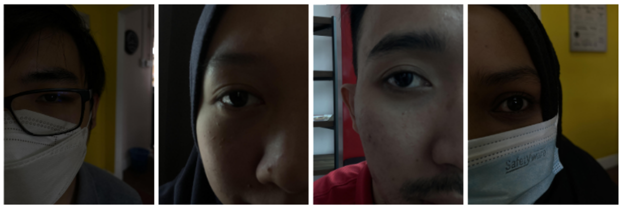

Fig. 2. Sample iris images from MIREIS dataset.

B. Fuzzification

Image enhancement with fuzzification involves the transformation of gray-level intensities of an image onto a fuzzy plane using membership functions. In addition to mapping the fuzzy plane back to the grayscale intensities of the images, the membership functions are changed to improve contrast. Increasing the weight of the gray levels closest to the image's mean gray level over those further from it aims to produce an image with higher contrast than the original.

Theoretically, fuzzy set theory provides a fresh perspective on image interpretation. An image with dimensions of size pixels and L distinct gray levels may be conceptualized as an array of fuzzy singletons. Each singleton represents a pixel, and its membership value indicates its brightness relative to a set of brightness levels, $I = 0, 1, 2, \dots L-1$ [29]. Eq. (1) presents the fuzzy theory utilized in image enhancement, where I_{xy} denotes the pixel intensity, (x, y), while μ_{xy} denotes its corresponding membership value.

$$FT = \bigcup_{x=1}^{X}\bigcup_{y=1}^{Y}\frac{\mu_{xy}}{I_{xy}} with \mu_{xy} \subseteq [0,1] \tag{1}$$

The three phases of fuzzy image processing are membership functions, fuzzification, fuzzy inference system, and defuzzification. Fuzzification involves providing an image with one or more membership values based on intriguing features, such as sharpening, edginess, brightness, and similarity. Following the image transformation into fuzzification, the membership values are modified using an appropriate fuzzy method.

Defuzzification signifies a retransformation of the membership values into the gray-level plane. The grayscale levels must be blurred for the image histogram's location to handle grayscale uncertainty. It indicates that each gray level is given a certain degree of membership based on where it falls on the histogram. High membership values are generally given to bright pixels, and low membership values are assigned to black pixels.

C. Defuzzification

Contrary to fuzzification, image defuzzification converts a fuzzy image back into crisp values. The inverse transformation in Eq. (2) is calculated to produce the enhanced image, $I'(x, y)$, where T' represents the original inverse transformation, T, while $I'(x, y)$, represents the gray-level of the enhanced image.

$$I'(x,y) = T'(I(x,y)) = (\bigcup_{x=1}^{X}\bigcup_{y=1}^{Y} I(x,y) \times (L-1) \tag{2}$$

D. Fuzzy Inference System

The fuzzy inference system comprises an expert's knowledge base, consisting of IF-THEN rules. The compositional rule establishes the mapping between fuzzy inputs and outputs, as presented in Fig. 3. The rules set in the proposed algorithms are as follows,

1) IF input is Very Dark THEN output is Extremely Dark
2) IF input is Dark THEN output is Very Dark
3) IF input is Slightly Dark THEN output is Dark
4) IF input is Slightly Bright THEN output is Bright
5) IF input is Bright THEN output is Very Bright
6) IF input is Very Bright THEN output is Extremely Bright

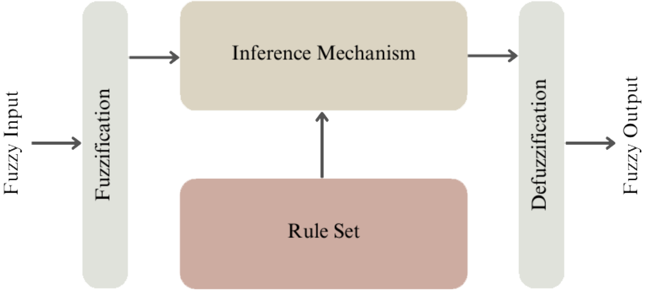

Fig. 3. The fuzzy inference system for this study.

This study involves eight rules for iris image enhancement, such as Extremely Dark (ED), Very Dark (VD), Dark (Da), Slightly Dark (SD), Slightly Bright (SB), Bright (Br), Very

Bright (VB), and Extremely Bright (EB). Fig. 4 illustrates the gray levels space derived from the membership functions for iris image enhancement. The rules are developed using the fuzzy sets specified in the gray levels ranging from [-50, 305] to [0, 255].

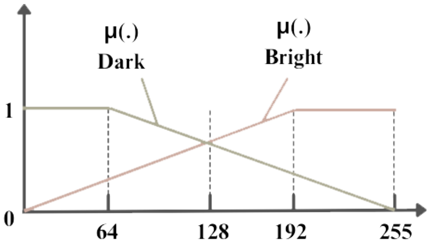

Fig. 4. The gray levels space based on the fuzzy sets.

E. Modified Gaussian Membership Functions

GMF comprises fuzzification, rule-based enhancement, and defuzzification. GMF quantifies the level to which pixel intensities belong to different iris regions. It transforms the initial data into a Gaussian distribution. The membership decreases as input values move further from the midpoint in positive and negative directions. The midpoint of the normal distribution, which is assigned to one, offers an optimal condition for the set.

Membership in the set decreases for input values, beginning at the midpoint and continuing until it diverges significantly from the optimal condition. At this point, it is deemed outside the set and is assigned zeros. The GMF can be computed in Eq. (3), where x is the input value of the GMF for set A, σ is the standard deviation, and c denotes the mean of the Gaussian function.

$$\mu_A(x;\sigma,c) = \exp\frac{-(x-c)^2}{2\sigma^2} \tag{3}$$

Following the fuzzification process, each intensity level, A, is assigned a corresponding fuzzy membership value $\mu(A)$ in the image. The attribute, such as bright or dark, is correlated with the intensity. The modification of GMF involves fine-tuning the fuzzy membership values assigned to each intensity level in the image. This modification enhances the image by increasing lighting on specific elements.

A function, $f(\mu(A))$, is selected to modify the membership values. This function varies according to the type of enhancement required. The modification function is applied to an individual's membership value. The modified value of intensity A, denoted as $f(\mu(A))$, is obtained by applying a function f on the original membership value $\mu(i)$. The function $f(\mu(A))$ affects membership values. An enhancement function can be:

$$f(\mu(A)) = \mu(A)^\gamma \tag{4}$$

The parameter γ determines the features of the enhancement:

- When γ is less than 1, the function extends the range of membership values, increasing contrast.
- When γ is greater than 1, the function compresses the membership values, reducing the contrast of specific intensity ranges.

Upon implementing this modification, the image's histogram receives a significant reshaping. The reshaping process is defined by fuzzy logic concepts and is characterized by a higher level of detail than conventional HE. The final stage in the procedure (distinct from the modification phase but essential for achieving the improvement) involves pairing these modified membership values with the corresponding pixel intensities.

F. Image Enhancement Methods

Image enhancement can be crucial due to poor image quality, including lighting, noise, high brightness or darkness levels, lack of sharpness, and blurriness. The image enhancement methods may reduce the analysis process that involves comprehensive image extraction. A low-quality image has distortions, such as an image that is not visible due to low lighting.

1) Advanced fuzzified histogram equalization: AFHE is an advanced approach used in image processing to boost brightness and improve the level of detail in images. The advanced version of the conventional HE method incorporates ideas of fuzzy logic. AFHE enables a more refined and situation-specific modification of image brightness in comparison to conventional HE. By transforming the original image into a uniform histogram, AFHE effectively improves the image's contrast. AFHE produces a significant global enhancement but may diminish the image's local details.

The AFHE provides the relationship in gray level and its corresponding frequency, which produces a gray image $G(i)$ as expressed in Eq. (5).

$$G(i) = \frac{n_i}{TN}, i = 0, 1, ..., L-1 \tag{5}$$

Let i represent the image's gray level, n_i be the number of pixels comprising gray level, and TN denotes the total number of pixels in the image. The histogram represents the probability distribution function of i. Eq. (6) expresses the HE, which can be accomplished based on $G(i)$.

$$h_k = Tf(r) = (L-1)\sum_{i=0}^{k} G(i) \tag{6}$$

Let the mapping function, $Tf(r)$, be denoted as h_k, and transform each pixel value k from the input image to h_k. L denotes the gray level of an output image. The histogram can receive a more even image intensity distribution with this modification. As a result, regions with lower local contrast can achieve higher contrast without compromising global contrast.

2) Contrast limited adaptive histogram equalization: CLAHE is a method for enhancing local contrast in an image. The image is acquired locally by forming some symmetrical grids, referred to as the region size. Three markers identify the image's regional structure: the corner region (CR) designates the areas in the image's corner, the border region (BR) designates the areas around the image that keeps the CR, and the inner region (IR) designates the remaining areas in the center.

CLAHE, which involves placing a boundary value on the histogram, can be used to solve the issue of excessive contrast enhancement. This limit value, which indicates a histogram's maximum height, is the clip limit. Eq. (7) defines how to compute a histogram's clip limit.

$$\beta = \frac{T}{L}(1 + \frac{\alpha}{100}S_{max}) \tag{7}$$

Let T denotes the pixel count of each block, and L indicates the block's gray level. While α is the clip factor and $Smax$ is the maximum slope.

3) Fuzzy contrast enhancement: The FCE aims to create dark pixels that are darker and bright pixels that are brighter to improve the image. Eq. (8) computes the FCE.

$$F \leftarrow h(x) + \sum_{x}\sum_{y}\mu_{F(x,y)'} \tag{8}$$

The FCE is an integer series, denoted as $h(x)$, where x ranges from 0 to $L-1$. In this context, $h(x)$ represents the frequency at which gray levels within x occur. The fuzzy histogram is constructed by viewing the gray value $f(x,y)$ as a fuzzy number $\mu_{F(x,y)'}$. While $\mu_{F(x,y)}$ represents the fuzzy membership function. Fuzzy logic is more adept at managing values' imprecision than traditional crisp values. Thus, it yields a smooth histogram.

G. Performance Measurement

PSNR is a quantitative indicator that reflects how much an image's quality was reduced throughout the compression or processing processes. It measures the ratio between the maximum signal value and the amount of noise in the image using decibels (dB). This study employed PSNR to compare the quality differences between the original and enhanced images. Image quality is evaluated based on the PSNR value, which a higher PSNR value indicates a high-quality image.

The mean-squared error (MSE) is initially computed in Eq. (9) to obtain the PSNR, where I_1 is the enhanced iris image, I_2 is the original iris image, and X and Y are the numbers of rows and column in the input iris image.

$$MSE = \frac{\sum_{X \times Y}[I'(x,y) - I(x,y)]^2}{X \times Y} \tag{9}$$

Eq. (10) calculates the PSNR value, where Z represents the maximum variation in the data type of the input iris image. Z equals one if the input image is a double-precision floating-point; otherwise, Z is 255.

$$PSNR = 10\log_{10}\frac{Z^2}{MSE} \tag{10}$$

IV. Result and Discussion

All experiments used Google Colaboratory to analyze the iris image enhancement methods: AFHE, CLAHE, and FCE. PSNR, a prevalent metric for assessing image quality, was employed to evaluate the efficacy of the iris image enhancement methods. This study also measures the total CPU times for each method to determine which image enhancement method works faster for 24 iris images. The relationship between the PSNR value and the CPU times shows the effectiveness of the image enhancement methods. Therefore, it can identify which image enhancement method works best for iris images.

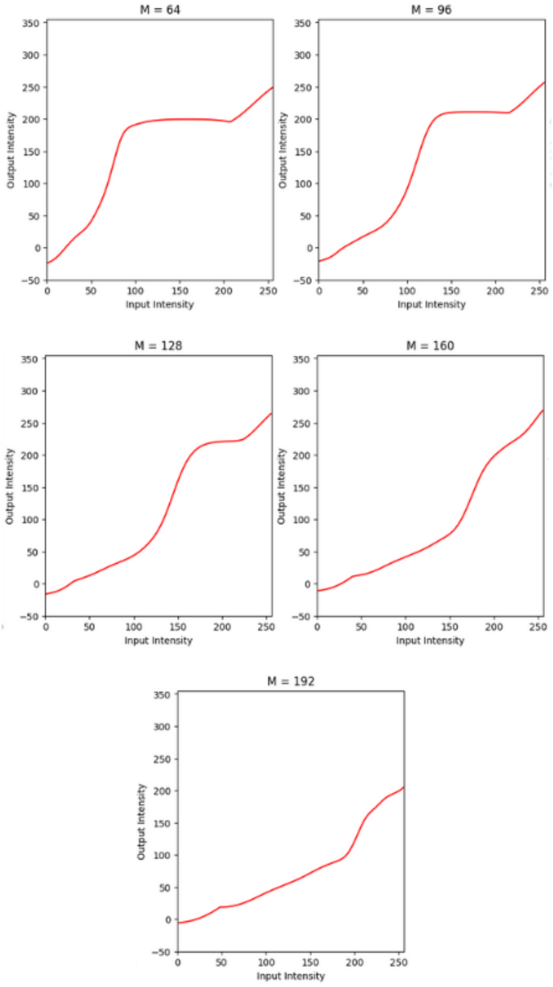

Fig. 5. The input and output intensity for $M = 64$, $M = 96$, $M = 128$, $M = 160$, and $M = 192$.

Fig. 5 shows the input and output intensities of 24 iris images to map the gray level. The range of the pixel intensity value is 64 for minimum input pixel intensity to 192 for maximum input pixel intensity. The gray level for the output pixel intensity increases for intensity values of 64, 96, and 128 at the middle of the block, while the intensity values of 160 and 192 slightly decrease but remain constant to enhance the image's brightness. The results highlight how the image enhancement methods improve the visibility and contrast of iris images, thereby rendering them more appropriate for iris recognition systems used in non-cooperative environments.

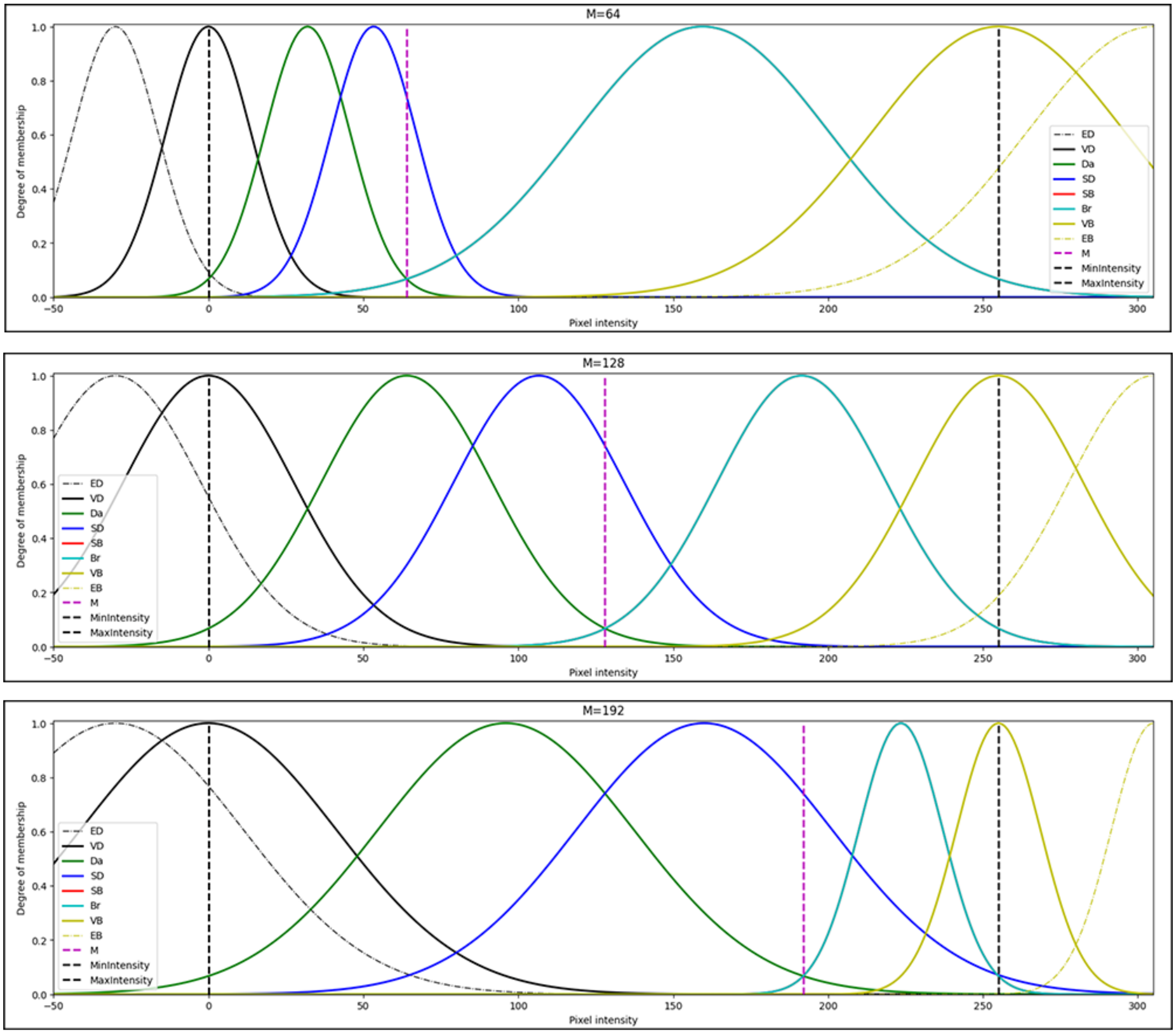

Fig. 6. The relationship between modified gaussian membership function, M and the pixel intensity based on the modified membership functions.

The fuzzy rule sets according to the IF-THEN rule were modified based on the input image. The maximum M used for iris images is six, while the minimum M is two. Fig. 6 demonstrates the relationship between the modified Gaussian membership functions and the pixel intensity based on the value in the selected membership functions, M. The image's brightness decreases and darkens when M equals 64. In addition, the pixel intensity also shows high contrast. The image becomes extremely bright when $M = 192$, with a maximum intensity between 192 and 255, respectively. Therefore, the image can contrast less to the $M = 64$. However, the high and low contrast is balanced when M is 128. The mid-range of the pixel intensity between 0 and 255 made the image not too dark and bright.

The analysis of the AFHE, CLAHE, and FCE depicted in Fig. 7 demonstrates that the image quality of AFHE outperforms those of CLAHE and FCE. The original images exhibit low lighting; hence, the enhanced images using AFHE preserves brightness better with low contrast. The AFHE could help the data annotation process for iris segmentation. CLAHE marginally brightens the image compared to AFHE; however, some areas continue to have high contrast, which makes the image slightly dark. Nevertheless, FCE demonstrates a significant difference in brightness levels, resulting in a darker appearance in some images. Some images merely enhance a low gray level, retaining the image in poor lighting.

Table I shows the experiment result of image enhancement methods (AFHE, CLAHE, and FCE) based on the PSNR. Enhanced image quality corresponds to a higher PSNR value. FCE has a higher PSNR value of 76.48db and longer CPU times at 13.9s. To be compared with AFHE, AFHE indicates the lowest PSNR value at 76.02db with faster CPU times at 4.04s. Although the PSNR value of HE is lower than CLAHE and FCE, it demonstrates better image quality, as depicted in Fig. 7, with faster CPU times.

AFHE enables more refined contrast enhancement, which is particularly beneficial in images with complex lighting settings or situations where simple histogram equalization can result in severe or insufficient enhancement. Fuzzy logic regulates

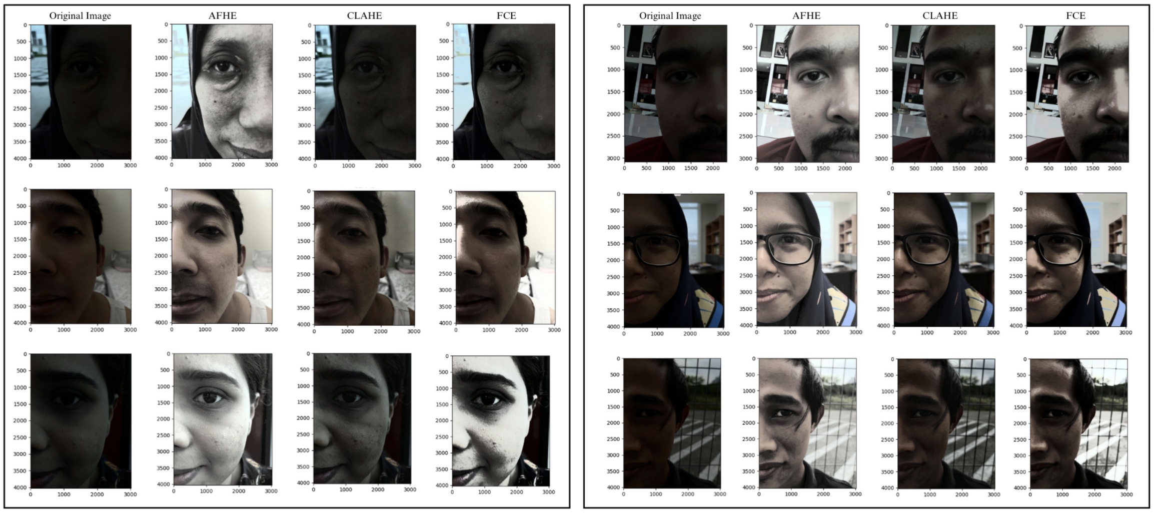

Fig. 7. Iris image enhancement results using AFHE, CLAHE, and FCE based on the low lighting conditions of original images.

TABLE I. Comparison of Iris Image Enhancement Methods with the PSNR Value

Enhancement Methods	PSNR (dB)	CPU Time (s)
AFHE	76.02	4.04
CLAHE	76.23	4.9
FCE	76.48	13.9

TABLE II. Comparison with State-of-the-art Methods

Author	Method	Evaluation Metric	Result
[15]	HE-FCM	Accuracy	0.86
	CLAHE-FCM		0.91
[1]	HE	PSNR	14.725
	AHE		14.148
	CLAHE		17.459
[18]	HE	MSE	18.25
		PSNR	28.87
[23]	HE	PSNR	16.76
	AHE		16.95
[28]	Gaussian	Accuracy	89.2
	Triangular fuzzy average		87.4
	Triangular fuzzy median		88.4
	HE		83.4
	CLAHE		84.8
This study	**AFHE**	**PSNR**	**76.02**
	CLAHE		**76.23**
	FCE		**76.48**

the enhancement, which helps retain details better and prevent errors frequently created by aggressive methods. Implementing fuzzy sets and rules enhances the method's adaptability to various image types and expected outcomes. Therefore, it can be concluded that AFHE is the best iris image enhancement method, followed by CLAHE and FCE, respectively, because AFHE preserves more brightness and provides a significant iris image quality.

The comparison with state-of-the-art methods is crucial for validating the effectiveness and benchmarking the performance of the proposed image enhancement techniques, namely AFHE, CLAHE, and FCE. Using PSNR as a measure evaluates the accuracy of the image enhancement in terms of pixel-level fidelity. The proposed approaches achieved higher PSNR values than existing state-of-the-art methods [1], [18], [23], as shown in Table II, indicating that AFHE, CLAHE, and FCE preserve image quality and reduce distortion throughout the enhancement process. PSNR is commonly employed to evaluate methods such as HE, CLAHE, and FCE that modify image brightness; however, it may not adequately measure perceptual quality or task performance. This limitation is highlighted by the accuracy results of previous studies in [15], [28], which demonstrate superior performance compared to AFHE, CLAHE, AHE, and FCE in terms of accuracy.

As different metrics may capture various aspects of image quality and utility, this inconsistency highlights the significance of employing multiple evaluation metrics to comprehensively evaluate the performance of image enhancement methods. Hence, while PSNR can indicate better pixel-level accuracy, accuracy metrics further explain enhanced images' perceptual quality and efficiency for specific applications. Further research could explore the development of comprehensive evaluation frameworks that consider a range of metrics to provide a more holistic assessment of image enhancement methods. Additionally, investigating the factors contributing to inconsistency between PSNR and accuracy metrics could yield valuable information for further improving the performance of image enhancement methods, ultimately enhancing their utility in practical applications.

V. Conclusion

This study presented fuzzified image enhancement methods, AFHE, CLAHE, and FCE, to enhance the quality of iris images, specifically for data annotation. The iris images in the MIREIS dataset provide some images with low lighting conditions, creating a challenging process during data annotation. Based on the input iris images, the Gaussian membership functions were modified to the suitable intensity value. The GMF followed the rule set in the fuzzy inference system for the fuzzification and defuzzification process. The AFHE is the best fuzzified image enhancement method compared to CLAHE and FCE based on the PSNR value and CPU times. The findings of this study can assist other researchers in data annotation, particularly in non-cooperative environments when iris images contain low lighting conditions. This study only employed image enhancement methods to modify the iris image's contrast and lighting. However, these approaches cannot reduce the presence of reflections in the iris image.

VI. Future Work

Further work can be focused on extending the study to include reflections in iris images, which were not adequately reduced by the image enhancement methods. Studies could focus on developing methods to precisely reduce or eliminate reflections in iris images captured in non-cooperative environments with low lighting. Further improving the effectiveness of the AFHE, CLAHE, and FCE approaches in data annotation tasks might be examining their ability to work with iris images at different distances and angles. This could offer significant data concerning the methods' robustness and efficacy in various conditions.

Moreover, combining several image enhancement methods or employing machine learning for modifying parameters adaptively might improve the effectiveness and flexibility of image enhancement methods. The effectiveness and application of AFHE, CLAHE, and FCE in iris image enhancement would be further advanced by addressing these issues and investigating these potentials for enhancement. It can support the improvement of iris recognition systems in non-cooperative environments.

Acknowledgment

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IMEO: Anomaly Detection for IoT Devices using Semantic-based Correlations

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***Abstract*—In the Internet of Things (IoT) security, anomalies due to attacks or device malfunctions can have serious consequences in our daily lives. Previous solutions have been struggling with high rates of false alarms and missing many actual anomalies. They also take a long time to detect anomalies even if they successfully detect anomalies. To overcome the limitations, this paper proposes a novel anomaly detection system, named IoT Malfunction Extraction Observer (IMEO), that utilizes semantics and correlation information for smart homes. Given IoT devices installed at home, IMEO creates virtual correlations based on semantic information such as applications, device types, relationships, and installation locations. The generated correlations are validated and improved using event logs extracted from smart home applications. The finally extracted correlations are then used to simulate the normal behaviors of the smart home. Any discrepancy between the actual state of a device and the simulated state is reported as abnormal while comparing correlations and event logs. IMEO also utilizes the observation that malfunctions of IoT devices occur repeatedly. An anomaly database is created and used so that repetitive malfunctions are quickly detected, which eventually reduces processing time. This paper builds a smart home testbed on a real-world residential house and deploys IoT devices. Six different types of anomalies are analyzed, synthesized, and injected to the testbed, with which IMEO's detection performance is evaluated and compared with the state-of-the-art correlation-only detection method. Experimental results demonstrate that the proposed method achieves higher performance of detection accuracy with faster processing time.**

***Keywords*—Security; anomaly detection; semantics; Internet of Things; attack**

I. Introduction

The rapid growth of Internet of Things (IoT) has enjoyed a wide variety of applications. According to a market report, the global number of connected IoT devices is expected to grow to up to 16.7 billion endpoints by the end of 2023 [1]. It also reports that this number will grow by 16% annually to reach 29.7 billion by 2027. IoT devices are increasingly being integrated through IoT platforms such as SmartThings [2] and Homekit [3]. This allows users to connect to IoT devices from different vendors using smart applications, thus providing great convenience for IoT heterogeneity.

With the development of IoT applications (this paper is specifically focused on smart homes), there are also growing security and safety concerns [4]. Various causes, including attacks, device errors, malfunctions, and misconfigurations, can cause anomalies in IoT and eventually lead to unexpected (and often unfavorable) outcomes. IoT anomalies have intrinsic properties, and followings show some examples of anomalies and consequences in smart homes. First, IoT devices can extend cyberspace attacks to the physical world. For instance, a "close the water valve" command can be blocked by an attacker, resulting in flooding of the room. Second, it is very often that the malfunction of the device is rarely noticed until a specific result occurs. An electronic heater that has received a "too cold" command from a smart home application can cause a fire due to the relay switch not being able to turn off the heater. Third, when IoT devices are connected to each other via automation, abnormal behaviors of one device can cause unwanted behaviors of other devices, which exacerbates the effects of the anomaly. For instance, a smart door lock that is automatically unlocked only when there are residents, is released due to false events by a human presence sensor.

To address these concerns, many previous research on anomaly detection utilize data mining techniques that profile normal behaviors of a system and report off-profile events as anomalies. These works generally accept event logs as inputs without fully considering semantics of each event that can actually be obtained from smart apps, device types, and device functions. There are three limitations to be considered in this approach. First, the logic in some smart apps is too complex to be accurately extracted, which may cause incorrect normal operations and malfunctions. Say, a smart app logic generates an event pattern, "If two motion sensors in a living room both do not detect movement, turn off the smart plug after 30 minutes". It is difficult to mind this when considering the 30-minute delay and the "AND" logic between two sensors. Therefore, it may not be possilbe to detect the anomaly, "a smart plug fails to turn off". Second, it is often difficult to interpret the learning results, making it difficult to explain them and thus confusing to users. Third, when configurations are changed, learning results are not updated quickly. A long retraining process is required to adapt to the changes, and a lot of false alarms occur before retraining is finished.

An intuitive approach to improve the accuracy of anomaly detection is to incorporate semantic information such as device types, installation locations, relationships, and automation logic. However, there are many technical challenges to be resolved to realize the approach. 1) Typical mining techniques accept event logs as inputs; however, representing a variety of semantic information in the form of event logs has not been studied. 2) Patterns extracted from event logs may conflict with those of system behavior derived from smart home applications; identifying and resolving these conflicts are not easy. 3) It is unknown how to update a system profiling effectively when a smart home application changes.

To overcome the challenges, this paper proposes IoT Mal-

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function Extraction Observer (IMEO), a new anomaly detection system for smart home applications. Technically, it constructs correlations by using semantic information, explaining how a device's states and events correlate with those in another device, and verifies them by using event logs as evidence. Given the correlations, IMEO simulates normal behaviors and compares the simulated states to those in a real world via contextual and consequential checkings. It then reports anomalies if finding inconsistencies in comparison. Because the correlations become explainable along with the semantics in IMEO, they can help resolve conflicts with smart home applications. Thanks to the explainability, the correlations can be updated with the changes of the smart home application. This paper implements a prototype of IMEO and builds a real-world smart home testbed consisting of three rooms. Then, experiments are conducted, and the results show that IMEO can reach a high precision of 99.33% and a recall of 95.35%, demostrating better performance than a prior method.

The rest of the paper is organized as follows. Section II summarizes possible anomalies that can occur in IoT environment. Section III reviews research works on anomaly detection for IoT. Section IV introduces a reference architecture for an IoT system and defines a threat model in the architecture. In Section V, three correlation channels and the representation of correlations are described. We present the proposed system in Section VI. Our testbed is implemented and experimented in Section VII, which is followed by evaluation in Section VIII. Finally, Section IX concludes the paper.

II. Anomalies in IoT

Previous works have reported that IoT devices are often unreliable and vulnerable to malicious attacks [5], [6], [7]. This section discusses anomalies in IoT caused by devices' malfunctions and attacks.

A. Malfunctions in IoT Devices

In general, IoT devices communicate with an IoT platform; they report any *event* records and receive *command* messages to/from the platform. This subsection categorizes malfunctions in terms of them.

1) Events: There are two types of causes related to event records. (i) *Faulty event* refers to devices' reporting incorrect values. This is mainly attributed to a device defect or physical inteference. For instance, a door knocking sensor goes active and then inactive without reason [8], and a motion detector sees motions in an empty room and turns on lights [9]. (ii) *Event loss or delay* represents that event records are not reported to the platform (or any server) in a timely manner. For instance, status updates from presence sensors have been reported to suffer from long delays [10]. This may cause significant delays in executing related automation when after a resident leaves home. If the update is lost, an automation rule may fail to lock a door while away.

2) Commands: There are cases inducing malfuntions on devices. (iii) *Bogus command* refers to a phenomenon called "poltergeist" frequently reported on a user forum [11]. For instance, users reported that lights or sensors turned on in the middle of the night. It is said that this phenomenon occurred in an office where no one was present or in the hallway of a house where everyone was sleeping. They also reported that a heater connected to an air conditioner suddenly reacted and turned on. (iv) *Command failure* represents that the IoT platform issues a command that is not executed on an IoT device. A physical problem or cyber problem may cause this. The physical problem is mainly attributed to a malfunction of an IoT device. For instance, if an electrical relay inside a smart plug is broken, it may prevent the plug from cutting off the power supply. The platform recognizes that the plug is turned off, though. The cyber problem includes unstable network connections and system crashes that prevent commands from being executed.

B. Attacks on IoT Devices

This subsection identifies potential vulnerabilities on IoT devices and discovers five different types of IoT attacks.

(i) *Fake event* is an event maliciously generated by an attacker. This can trigger an IoT device to behave unexpectedly, which can lead to unfavorable consequences [12]. For example, when the attacker injects an event indicating the presence of a fake person, a door lock is unlocked. (ii) *Event interception* by an attack can intercept and discard event records. For instance, the attack blocks the wireless connections of window and door sensors so that they stop sending event records, which can lead to a home security system fails to alarm [13]. (iii) *Fake command* is injected by by an attacker into an IoT device [14]. Say, smart speakers and smart switches may accept fake commands from a local network without authenticating sources [15], [16]. (iv) *Command interception*. An attacker can also intercept commands and prevent them from being delivered to IoT devices [17]. (v) *Compromised device*. An attack can gain access to an IoT device and perform the following attacks. In a "stealthy command", the attacker takes control of a device to execute commands and prevents corresponding feedback events from being sent in order to remain covert [18]. This is similar to the fake command, except that no feedback events are sent. "Denial of Execution" means that when a valid command is sent to the device, it does not execute the command and sends back a feedback event reporting that the command was executed.

C. Repeated Malfunctions of IoT Device

A user forum notes that users are frequently having trouble with malfunctions of specific IoT devices; devices that malfunctioned once malfunction repeatedly after that or cause other problems. For instance, a sensor once disconnected from a network once experienced multiple network disconnections over several days. As such, repeated malfunctions of the device can cause difficulties in operating the automation involved or problems that incorrectly trigger other actuators.

III. Related Works

With the advancement of IoT devices and the advent of home automation applications, security and privacy issues are attracting great attention. However, most research has focused on detecting threats, attacks, and malicious codes rather than IoT malfunctions. For example, HomeGuard [19] presents the first systematic classification of threats caused by interference between different automated applications, such as automation collisions, serial execution, and loop triggering. The authors propose a method to detect these threats using SMT (Satisfiability Modulo Theories) Solver, where it performs symbol execution to extract automation rules from an application. PFirewall [20] is a study that recognizes the continuous inflow of excessive IoT device data into an IoT automation platform. It protects users' personal information from the platform by minimizing data without changing the IoT device or platform. HoMonit [21] focuses on detecting smart home applications that are malfunctioning, unlike this work on detecting anomalies of IoT devices. Given a physical event, Orpheus [22] automates system call tracking and then checks for attacks via comparison. However, it is not possible to detect anomalies such as fake events and event intercepts.

Many previous studies allow anomaly detection systems to learn the normal behavior of smart homes from historical data. For example, SMART [23] trains activity classifiers for multiple users based on different subsets of sensor readings, and further trains another classifier that takes a vector of activity classification results as input to detect sensor failures. DICE [24] checks contexts in smart homes to detect anomalies during state transition.

Traditional mining-based solutions are not clear how they can accurately learn complex behaviors in smart homes. The main difference between these conventional anomaly detection systems and this work is that IMEO extracts various semantic information such as device types, device relationships, and smart home applications and injects the information into mining processes. IMEO is not only more accurate in detection, but each detected anomaly can be interpreted as violating the correlation, so it can be explained by itself.

IV. Threat Model

A. IoT System Architecture for Smart Homes

IoT devices in smart homes are increasingly integrated through IoT platforms for seamless automation. IoT integration platforms such as SmartThings, OpenHAB, and Amazon Alexa support automation programs. Although these platforms can handle numerous IoT devices, they are summarized as a small number of abstract devices. For instance, smart lights, regardless of their brands, shapes, sizes, or wireless technologies, are equally abstracted as light. Each abstract device has events and commands associated with it.

This paper considers SmartThings, one of the leading IoT integration platforms, for a system architecture for smart homes as it supports rich automation logic. A typical SmartThings deployment, as shown in Fig. 1, has a cloud-centric architecture consisting of four layers. At the top is SmartThings Cloud. It is a cloud where smart apps run and interact with abstracted functions. The cloud uses various communication techniques such as Wi-Fi, Zigbee, and ZWave to communicate with IoT devices through the network connection layer. IoT devices can be divided into cyber and physical parts. The cyber part manages the interface for humans and connects communication between the cloud and the physical part, while the physical part performs its functions in the physical world. For instance, the Philips' Hue smart bulb consists of a physical part of an LED bulb and a cyber part of a microcontroller with a built-in wireless component.

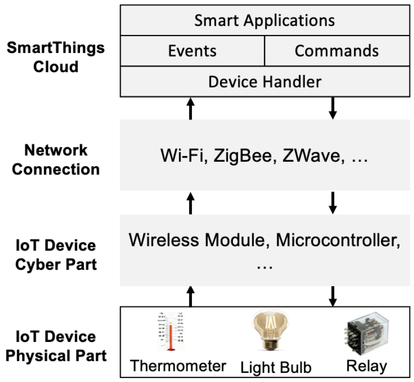

Fig. 1. IoT System architecture for smart homes; SmartThings.

Terms used in the SmartThings are briefly described in the following. An IoT device has one or more instrumental capabilities that are classified as actuators or sensors. Each capability defines one or more attributes. For instance, a smart plug device has a "switch" attribute and optionally a "power" attribute. The state (value) of each attribute is stored in the cloud and updated by events transmitted from the IoT device. For instance, a multi-purpose sensor has a capability of "contact sensor", and the cloud changes the state of its attribute "contact" from "open" to "closed" when it receives an event "contact closed" from the sensor. In the case of an actuator, SmartThings ensures that the state of the its attribute is udpated by a feedback event transmitted by the IoT device after a command is executed by the actuator.

B. Threat Model

This paper focuses on detecting malfunctions and attacks in IoT devices described in the previous section and on reporting repeated malfunctions immediately. It is also noted that IMEO is able to detect attacks that violate correlations. Attackers who know the correlations can avoid our detection by constructing an attack that does not violate the correlations.

Our threat model assumes that the IoT platform is not compromised. As with other anomaly detection tasks, we assume that there is no or few anomalies during training. No malicious or conflicting rules in installed smart home applications are also assumed. It is predicted that the average household could have more than 500 IoT devices in the near future [25]. Therefore, considering dense deployments, we propose to leverage scenarios where IoT devices have one or more other devices nearby to interact with and leverage this to detect abnormal physical behavior of the devices.

V. Correlations

IoT devices instrumented in the same home may be interrelated in the form of simultaneous or temporally related events [26], [27], [28], [29]. These correlations can occur due to the execution of application, physical interactions, or user activities. This section investigates causes of these correlations and classifies them into three channels as shown in Fig. 2. It also defines their representations.

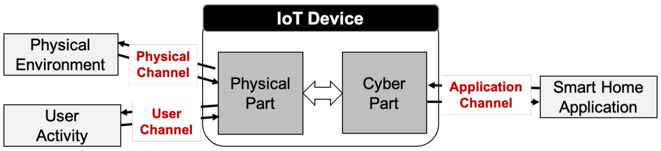

Fig. 2. Three correlation channels for IoT devices.

A. Correlation Channels

1) Application channel: Smart home applications directly cause correlations between triggers and actions as programmed. But, it also induces some additional correlations implicitly. For instance, in the SmartThings application, each automation rule implies a correlation worth verifying.

2) Physical channel: Two devices can be interrelated via certain physical properties. First, when an actuator takes an action it changes a physical property, which can be detected by a nearby sensor. For instance, an illuminance sensor can be affected by a nearby smart light turning on or off. Second, different sensors can be affected by the same physical event, creating temporally correlated IoT events. For instance, a door opening inevitably involves movement of the door, which captures an acceleration sensor and a contact sensor installed on the door, causing corresponding events to occur sequentially. As IoT device types increase, physical channel correlations can be widely observed across a variety of physical characteristics such as lighting, power, sound, and temperature.

3) User activity channel: A user activity gives rise to changes on a device, and the states of devices also reflects user activities. Thus, the user activity channel can lead to correlations between devices. For instance, when a TV is turned on it means that a user is nearby, and the motion sensor must detect it. When a user returns home, there must be continuity in events such as “person presence” showing the user’s movements and “contact sensor open” showing a front door opening.

B. Representation of Correlations

This paper represents an *event* and a *state*. Let denote $E_a^{\alpha(A)}$ an event reporting that the attribute α of device A should change to value a and $S_b^{\beta(B)}$ a state indicating that the attribute β of device B has value b. Based on them, it defines two types of correlations as below.

1) Event-to-Event (E2E) correlation: represents that an event should be followed by another. For instance, E2E correlation $\langle E_{active}^{motion(A)} \rightarrow E_{on}^{switch(B)} \rangle$, given motion sensors A and light B, indicates that an active event $E_{active}^{motion(A)}$ should be followed by another event $E_{on}^{switch(B)}$.

2) Event-to-State (E2S) correlation: represents that an event occurring means that a state is true. For instance, E2S correlation $\langle E_{high}^{power(Plug)} \rightarrow S_{on}^{switch(heater)} \rangle$ indicates that the state $S_{on}^{switch(heater)}$ should be true, when an event $E_{high}^{power(Plug)}$ occurs.

3) State-to-Event (S2E) correlation: represents that an event occurs only when a state satisfies a true condition. For instance, S2E correlation $\langle S_{>60}^{illuminance} \rightarrow E_{off}^{smartplug} \rangle$ indicates that the event $E_{off}^{smartplug}$ occurs only when the state $S_{>60}^{illuminance}$ becomes true.

4) Coditional (AND) correlation: represents that events and states are combined with conditions using the $\wedge$ symbol. For instance, a correlatin $\langle E_{active}^{Motion} \wedge S_{present}^{Presence} \rightarrow E_{on}^{Switch(Light)} \rangle$ represents that an event E_{active}^{Motion}, only when a state $S_{present}^{Presence}$ is true, should be followed by another event $E_{on}^{Switch(Light)}$.

VI. Proposed System: IMEO

This section proposes a novel anomaly detection system, named IoT Malfunction Extraction Observer. Fig. 3 demonstrates an overall architecture of the proposed system, and the followings describe operation steps. IMEO first generates correlations regarding three channels hypothetically by using a smart home application and Natural Language Process (NLP) techniques. We note that SmartThing is used for our application. It also receives event logs from the application that are then used to verify the correlations. Only correlations that have passed verification are used to detect anomalies. Upon receiving event logs in real time, it checks them through verified correlations. When an event log does not match correlations, it reports the event as an anomaly. IMEO reuses the detection results for better performance. It saves details of identified anomalies and maintains an anomaly history. Upon reoccurring the same malfunction, it can detect the anomaly directly from the history, instead of performing the correlation matching process.

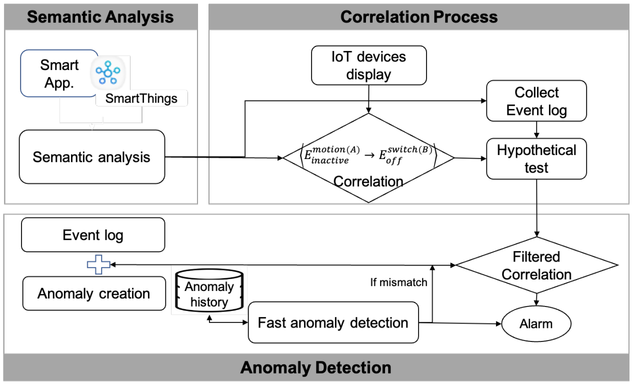

Fig. 3. System architecture of the proposed IMEO system.

A. Analyzing Semantics

The semantic analysis module first extracts semantics from the smart home application and then converts them to correlations (of application channels). To capture semantics, it investigates automation logics and related configurations, such as a temperature threshold in an air conditioner, in the application. For instance, given a semantic telling “Turn off the smart plug when illuminance is greater than 60,” an E2E correlation $\langle E_{>60}^{illuminance} \rightarrow E_{off}^{smartplug} \rangle$ is generated. This can also be represented by an S2E correlation $\langle S_{>60}^{illuminance} \rightarrow$

$E_{off}^{smartplug}\rangle$. It is noted, however, that the S2E correlation does not guarantee to be true necessarily and has to be verified in the following step.

B. Mining Correlations

There are many pattern mining methods, but few achieve both good usability and high accuracy in the context of smart home applications. Supervised mining methods are more accurate, but often require well-annotated data sets or user interventions. Unsupervised mining methods can be applied to unannotated data, but they are less accurate.

To overcome limitations of existing methods, this paper proposes a semantic-based mining method. Semantic information includes device type and installation location, which can be obtained from a smart home application. Based on this semantic information, IMEO generates virtual correlations corresponding to physical channels and user activity channels. Each virtual correlation is then independently verified. This paper assumes that there will be no or very few anomalies in the training phase, as with other anomaly detection tasks.

1) Processing event logs: It is necessary to preprocess event logs for two reasons as follows. First, repetitive sensor readings introduce noise into raw event log data. For instance, some power meters periodically report similar but slightly fluctuating measurements. Second, numerical readings of a device cannot be incorporated into logical calculations. Therefore, our preprocessing module eliminates duplicated records and transforms numerical data to binary information. To this end, the module applies the Jenks natural breaks algorithm [30] to the remaining readings and classify them as *low* or *high*. Then, it looks at the events for a given attribute on each device and removes events that do not continuously change state. Finally, two temporally adjacent events for the same attribute of the device have opposite values. However, our measurement observed that there were values whose differences were too small to be binarized using the Jenks natural breaks algorithm. So, these values were all added up to find the average value. Based on this, a value was classified into *low* if it was lower than the average value, and classified into *high* if it was greater than the average value .

2) Generating virtual correlation: In addition to E2S correlations generated from the application channels, correlations can be generated with other semantic information such as device attributes and relationships between attributes in the physical and user activity channels. To this end, semantic information is utilized to construct a table displaying correlated attribute pairs, and then each pair is filled with devices with matching attributes to create a correlation.

For physical channel correlations, IMEO sets up seven physical properties (illuminance, sound, temperature, humidity, vibration, power, and air quality) related to IoT devices in smart home environment. An NLP technique is used to determine whether the attributes of two IoT devices can be associated through physical properties. To obtain IoT abstract attributes, we refer to the description from the SmartThings developer site [31]. In order to objectively evaluate the relevance between attributes and physical properties, Google's word2vec model [32] is used to calculate the semantic similarity score between each word in the list and the physical properties. Then, this score is used as the *correlation score* between the physical property and attribute. The top 10 attributes with the highest scores for each physical property are considered to be interrelated through the corresponding physical properties.

Attributes that represent users' characteristics can be expressed as *presence* and *motion*. Since IoT devices are always influenced by users, it is natually assumed that all attributes related to each physical properties in the physical channel are related to users. User activity channel correlations are formed by considering that each physical property has a correlation with *presence* and *motion*.

Eventually, IMEO can find attribute pairs considered to be correlated with each other, from which it is possible to identify all the attributes of IoT devices installed in a smart home environment. Given a pair of two correlated attributes α and β on device A and B, respectively, IMEO generates four E2E correlations $\langle E_a^{\alpha(A)} \rightarrow E_b^{\beta(B)}\rangle$, $\langle E_{a'}^{\alpha(A)} \rightarrow E_b^{\beta(B)}\rangle$, $\langle E_a^{\alpha(A)} \rightarrow E_{b'}^{\beta(B)}\rangle$, $\langle E_{a'}^{\alpha(A)} \rightarrow E_{b'}^{\beta(B)}\rangle$, and four E2S correlations $\langle E_a^{\alpha(A)} \rightarrow S_b^{\beta(B)}\rangle$, $\langle E_{a'}^{\alpha(A)} \rightarrow S_b^{\beta(B)}\rangle$, $\langle E_a^{\alpha(A)} \rightarrow S_{b'}^{\beta(B)}\rangle$, $\langle E_{a'}^{\alpha(A)} \rightarrow S_{b'}^{\beta(B)}\rangle$. Symmetrically, eight correleations can also be generated with events on $\beta(B)$ leading the correlations.

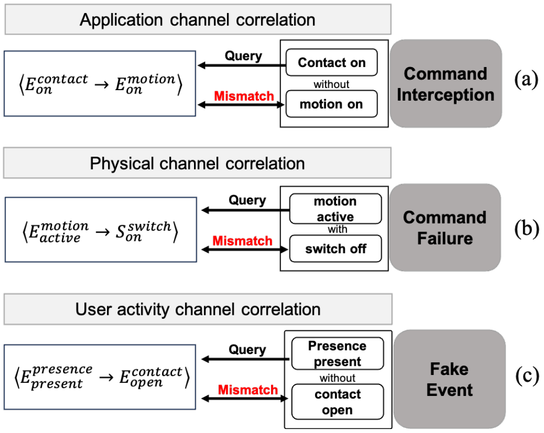
Application channel correlation
$\langle E_{on}^{contact} \rightarrow E_{on}^{motion}\rangle$
Query
Mismatch
Contact on
without
motion on
Command Interception
(a)
Physical channel correlation
$\langle E_{active}^{motion} \rightarrow S_{on}^{switch}\rangle$
Query
Mismatch
motion active
with
switch off
Command Failure
(b)
User activity channel correlation
$\langle E_{present}^{presence} \rightarrow E_{open}^{contact}\rangle$
Query
Mismatch
Presence present
without
contact open
Fake Event
(c)

Fig. 4. Anomaly detection process with three examples.

C. Detecting Anomalies

IMEO detects anomalies via two checking processes; *contextual check* and *consequential check*. The contextual check determines anomalies with E2S correlations. Suppose there is a correlation that a switch is *on* only when a motion sensor is *active* as shown in Fig. 4(b). Upon detecting the switch is *off* when the sensor is *active*, IMEO finds that this violates the correlation and determines to be an anomaly. The consequential check sees whether the next event occurs within 60 seconds when the preceding event of an E2E correlation occurs. If the next event occurs within the time boundary, the correlation is judged to be correct. For instance, Fig. 4(a) shows a correlation telling that an event "a contact sensor is *on*" should be followed by another event "a motion sensor is *on*". IMEO considers it normal if the motion sensor changes to on within 60 seconds after the contact sensor is turned on. It determines it to be abnormal if the motion sensor does not turn on within 60 seconds.

IMEO also performs a fast anomaly detection process. This is based on the feature, which has been frequently reported in user forums, that IoT devices malfunction repeatedly once malfunctioned. IMEO makes use of the feature to speed up the detection process while not sacrificing detection accuracy performance. Upon detecting an anomaly (i.e., a mismatch between an event log and correlation(s)), the anomaly detection module records a pair of event log, correlation(s) in a database of anomaly history. When the same malfunction occurs later, the module searches for the database and immediately determines if the event is abnormal before going through the checking processes. Once identified as anomaly this time, the resulting pair data is also recorded in the database. The number of repeated occurrence for each record is also saved in the database. Once sorted efficiently, this information can help accelerate the search process. Considering the repetition property of IoT devices, the fast anomaly detection process is expected to reduce detection time meaningfully.

VII. Experimental Setup

In order to evaluate the proposed IMEO system, we have built a real-world testbed as shown Fig. 5. Data was collected for three weeks to obtain event logs of IoT devices required for training and for one week for testing. We have applied correlations verified through the collected data to every events, from which the performance of IMEO is evaluated.

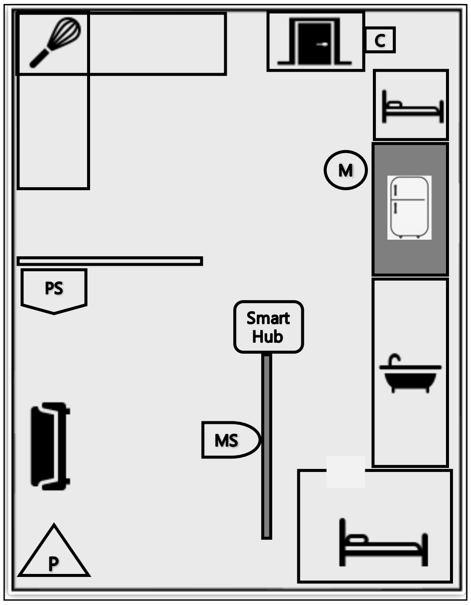

Fig. 5. Deployment layout of IoT devices.

A. Preliminary

1) Testbed: We have deployed IoT devices in a testbed of a private house consisting of three rooms and used Samsung SmartThings as an application. There are four residents in the testbed; one undergraduate student and three ordinary family members (two women and one man) who go to work during the day and returns home at night. None of them had any experience of using a smart home automation system. Residents are allowed to set automation of their interests that is fulfilled by IoT devices compatible with our smart home application. They are also given enough time to get used to the installed automation system before collecting data.

TABLE I. A List of IoT Devices Deployed in the Testbed

Device name	Attributes	Deployment	Abbr.
Motion Sensor (SmartThings)	motion	on wall	M
Multi Sensor (SiHAS)	motion, illuminance, humidity, temperature	on wall	MS
Contact Sensor (SmartThings)	contact, acceleration	on doors	C
Smart Button (SmartThings)	room control unit	on wall	PS
Smart Plug (SmartThings)	switch, power	as light lamp	P

2) IoT devices: Our testbed are deployed with five different types of IoT devices. Fig. 5 illustrates a deployment layout of devices, and Table I describes details of the devices including abbreviations. The motion sensor (denoted as M) is placed in the living room to detect the presence and motion of residents. The multi-function sensor (denoted as MS) is an IoT device that can detect human movements and perform a variety of roles, including detection of illumination, humidity, and temperature. The contact sensor (denoted as C) is able to detect the opening and closing of the front door. It can be used as a factor to determine whether residents are inside the house. The smart button (denoted as PS) is able to control the operation of smart devices in the testbed by unit. It can also check the temperature of the testbed. The smart plug (denoted as P) is a power plug used to control electrical devices.

TABLE II. Automation Rules Extracted from the Application

Index	Automation rules
R1	If (illuminance <30), then smart plug (on).
R2	If (illuminance >400), then smart plug (off).
R3	If C (opened) and MS (detected) for 15 minutes, then TV (on).
R4	If C (opened) and MS (undetected) for 20 minutes, then TV (off).
R5	If C (opened) and M (undetected) for 15 minutes, then P (off).
R6	If PS (pressed), then toggle TV
R7	If PS (double pressed), then toggle P.
R8	If PS (held), then turn off TV, air conditioner and P.
R9	If (illuminance <5), then TV (off).

3) Automation rules: We have extracted nine automation rules from the installed smart home application in the form of “automation operation if conditions arise”. The extracted rules of the test bed are listed in Table II.

4) Ethical concerns: All participants are fully aware of installed devices and the application. Experiments did not use sensitive devices such as cameras or microphones. All the data collected was considered as sensitive personal identification information and thus was removed immediately after experiments. For testing purposes, anomalies are generated intentionally and injected into the event log (see Section VII-C). To avoid safety issues, the injected anomalies did not target safety-sensitive devices. We notified participants that there might be some deviation from existing automated rules, but did not disclose the details of the anomalies (e.g. device and time). In addition, participants were advised to maintain a normal lifestyle and not panic if abnormalities were found. The purpose of maintaining their lifestyle habits is to avoid biasing their behavioral during experiments. Details of injected anomalies were presented to participants after testing.

TABLE III. A Partial List of Verified Correlations Obtained from the Testbed

ID	Correlation
$\mathcal{C}1$	$\langle E^{illuminance(\mathsf{MS})}_{<30} \rightarrow E^{power(\mathsf{P})}_{on}\rangle$
$\mathcal{C}2$	$\langle E^{illuminance(\mathsf{MS})}_{>400} \rightarrow E^{power(\mathsf{P})}_{off}\rangle$
$\mathcal{C}3$	$\langle E^{contact(\mathsf{C})}_{open} \wedge E^{motion(\mathsf{M})}_{detect} \rightarrow E^{TV}_{on}\rangle$
$\mathcal{C}4$	$\langle E^{contact(\mathsf{C})}_{open} \wedge E^{motion(\mathsf{M})}_{undetect} \rightarrow E^{TV}_{off}\rangle$
$\mathcal{C}5$	$\langle E^{contact(\mathsf{C})}_{open} \wedge E^{motion(\mathsf{M})}_{detect} \rightarrow E^{switch(P)}_{off}\rangle$
$\mathcal{C}6$	$\langle E^{humidity(\mathsf{MS})}_{<40} \rightarrow S^{contact(\mathsf{C})}_{close}\rangle$
$\mathcal{C}7$	$\langle E^{humidity(\mathsf{MS})}_{>60} \rightarrow S^{contact(\mathsf{C})}_{close}\rangle$
$\mathcal{C}8$	$\langle E^{acceleration(\mathsf{C})}_{on} \rightarrow E^{motion(\mathsf{MS})}_{detect}\rangle$
$\mathcal{C}9$	$\langle E^{contact(\mathsf{C})}_{open} \rightarrow E^{motion(\mathsf{M})}_{detect}\rangle$
$\mathcal{C}10$	$\langle E^{motion(\mathsf{M})}_{detect} \rightarrow E^{contact(\mathsf{C})}_{open}\rangle$
$\mathcal{C}11$	$\langle E^{motion(\mathsf{MS})}_{active} \rightarrow E^{switch(\mathsf{P})}_{on}\rangle$
$\mathcal{C}12$	$\langle E^{acceleration(\mathsf{C})}_{active} \rightarrow E^{contact(\mathsf{C})}_{closed}\rangle$
$\mathcal{C}13$	$\langle E^{illuminance(\mathsf{MS})}_{<5} \rightarrow E^{power(TV)}_{off}\rangle$
$\mathcal{C}14$	$\langle E^{button(\mathsf{B})}_{held} \rightarrow E^{airconditioner}_{off}\rangle$
$\mathcal{C}15$	$\langle E^{button(\mathsf{B})}_{held} \rightarrow E^{power(TV)}_{off}\rangle$
$\mathcal{C}16$	$\langle E^{button(\mathsf{B})}_{held} \rightarrow E^{switch(\mathsf{P})}_{off}\rangle$
$\mathcal{C}17$	$\langle E^{power(\mathsf{P})}_{low} \rightarrow S^{switch(\mathsf{P})}_{off}\rangle$
$\mathcal{C}18$	$\langle E^{power(\mathsf{P})}_{high} \rightarrow S^{switch(\mathsf{P})}_{on}\rangle$
$\mathcal{C}19$	$\langle E^{switch(\mathsf{P})}_{on} \rightarrow E^{power(\mathsf{P})}_{high}\rangle$
$\mathcal{C}20$	$\langle E^{motion(\mathsf{M})}_{detect} \wedge E^{contact(\mathsf{C})}_{open} \rightarrow E^{contact(\mathsf{C})}_{close}\rangle$
$\mathcal{C}21$	$\langle E^{contact(\mathsf{C})}_{open} \wedge E^{motion(\mathsf{M})}_{undetect} \rightarrow E^{switch(\mathsf{P})}_{off}\rangle$
$\mathcal{C}22$	$\langle E^{motion(\mathsf{MS})}_{detect} \rightarrow S^{switch(\mathsf{P})}_{on}\rangle$
$\mathcal{C}23$	$\langle E^{motion(\mathsf{MS})}_{undetect} \rightarrow S^{switch(\mathsf{P})}_{off}\rangle$
$\mathcal{C}24$	$\langle E^{motion(\mathsf{MS})}_{detect} \rightarrow S^{contact(\mathsf{P})}_{closed}\rangle$

B. Training for Testing

1) Training IMEO: In the testbed, 14 E2E correlations are generated from the automation rules. Additionally, it generates 10 E2S correlations in the application channel, 749 correlations in the physical channel, and 417 correlations in the user activity channel, for a total of 1,176 correlations. Then, they are verified using 20,002 event logs collected during the three-week training phase. A total of 96 correlations passed the verfication test. Table III lists portions of the verfied correlations.

2) Findings: Belows share some interesting obervations from the testbed.

O1. While C is a contact sensor, it has an additional correlation, $\mathcal{C}12$= $\langle E^{accelation(\mathsf{C})}_{acitve} \rightarrow E^{contact(C)}_{closed}\rangle$. This implies that an event $E^{accelation(C)}_{acitve}$ is followed by another event $E^{contact(C)}_{closed}$, explaining that a front door (C) usually closes immediately after it opens.

O2. The E2S correlation $\mathcal{C}18$ indicates that the power of P is high only when P is on.

O3. The smart plug P turns a light on and off. Each time P is turned on, the power usage increases (see $\mathcal{C}19$ in the table).

O4. Physical and user activity channel correlations cannot be obtained without mining because they are not included in the application. On the other hand, there are correlations that can be easily extracted from the application but are difficult to mine. For instance, it is difficult to mine correlations that involve delays accurately, but their relations can be derived from rules like R3, R4, and R5.

3) Baseline: This research selects a correlation-only detection method [33], [34], [35] as a baseline approach, because it has been widely used for anomaly detection and is a well-established for mining correlations and rules. It is noted that IMEO is also based on correlation mining. For comparison, the correlation-only method is performed on the same data collected from our testbed.

TABLE IV. A List of Anomalies Selected and Simulated

Index	Anomaly type	Anomaly Creation Method
A1	Faulty/Fake events	To insert events into the data set
A2	Event loss/Interception	To remove events from the data set
A3	Bogus/Fake commands	To toggle from a bogus application
A4	Command failures(cyber)/ Command interception	To cut off devices' power supply
A5	Command failures(physical)	To cover bulbs with a paper
A6	Command failures(physical)	To unplug connected appliances

C. Generating Anomalies

To evaluate IMEO, six anomalies are simulated on the testbed as listed in Table IV. Because the same anomaly often occurs in IoT devices when malfunctions occur, six representative abnormalities are selected. To this end, we refer to the attacks from the literatures investigating IoT attacks and malfunctions frequently discussed in the Samsung SmartThings community. In order to simulate IoT devices as abnormal cases, event logs collected during the three-week training phase are arbitrarily modified. We also disrupt the automation rules, and resulting event logs are used to detect malfunctions. Tests are conducted multiple times for each malfunction. If an IoT attack has the same impact as a malfunction on event logs, we group and simulate it as one case. For instance, since faulty events due to sensor malfunctions and fake events due to attacks have the same impact, a total of 100 MS motion events are grouped and simulated by randomly injecting them into the test event log (see A1 in Table IV).

1) Faulty / Fake events: Events of devices such as motion sensors, presence sensors, and contact sensors are known to be unreliable, so we insert them to simulate the faulty/fake events.

2) Event loss / Interception: To simulate this, we randomly remove events on some devices from the test event log. We primarily select devices for which users have reported discomfort with event loss, such as multi-function sensors, contact sensors, and motion sensors.

3) Bogus / Fake commands: Users have frequently reported inconvenience that both smart lights and plugs have been unexpectedly turned on or off. To simulate these, a bogus application has been developed, that IMEO does not know about, and arbitrary commands to the appplication turn the smart plug on and off randomly.

4) Command failures (cyber) and Command interception: Our experiments simulate command errors and command interceptions in the cyber part of the smart plug. To this end, we make the power of target devices disconnected so that they are unable to respond to any commands. Experiments are conducted several times a day on each target device.

5) Command failures (physical): Command failures in the physical part are simulated in the multi-function sensor (illuminance) and the smart plug. The multi-function sensor is covered by blackout curtains, and appliances are physically unplugged from smart plugs. Two deivces still respond to commands with feedback events, but these commands have no physical effect. For each device, experiments are conducted several times a day.

VIII. Performance Evaluation

This section evaluates the performance of IMEO, the proposed anomaly detection system for IoT devices. First, it shows how correctly the proposed method can detect anomalies. Then, IMEO's performance is compared with the baseline approach (correlation-only detection method, COD) described in Section VII-B, which is followed by demonstration of overall performance in both methods. The last part evaluates the processing time of IMEO.

A. Evaluation Metrics

For evaulation, this paper uses the following metrics. Given the context of anomaly detection, *accuracy* is the ratio of event logs reported correctly (true anomalies and true normal events) to the entire events. *Precision* indicates the ratio of correctly detected anomalies to those reported to be abnormal (i.e., percentage of anomaly detection that is correct), and *recall* indicates the ratio of correctly detected anomalies to all the anomalies (i.e., percentage of anomalies that can be detected). *F1 score* is the harmonic mean of the precision and recall and represents the detection accuracy considering an imbalanced event situation where there are a relatively small number of anomaly events or vice versa.

$$
\begin{aligned}
Accuracy &= \frac{True\,Positive + True\,Negative}{All\,Events} \\
Precision &= \frac{True\,Positive}{True\;\,Positive + False\,Positive} \\
Recall &= \frac{True\,Positive}{True\,Positive + False\,Negative} \\
F1\,Score &= 2 \times \frac{Precision \times Recall}{Precision + Recall}
\end{aligned}
$$

B. Results of Anomaly Detection

Table V summarizes detection results of IMEO across six different anomaly types described in Section VII-C. For three out of six types, IMEO successfully detects all events. The following detection examples illustrate how IMEO detects anomalies.

TABLE V. Detection Results of IMEO Across 6 Different Types of Anomaly Events

Anomaly Index	# of instances	Precision	Recall	Correlation(s) violated
A1	100	98.97%	94.12%	$\mathcal{C}22$
A2	100	100%	100%	$\mathcal{C}12$
A3	100	97.02%	98%	$\mathcal{C}12$, $\mathcal{C}19$
A4	100	100%	100%	$\mathcal{C}11$, $\mathcal{C}12$
A5	30	100%	80%	$\mathcal{C}1$, $\mathcal{C}2$
A6	100	100%	100%	$\mathcal{C}17$, $\mathcal{C}18$

Detection 1. When entering the house, a resident is detected by the contact sensor C attached to the front door, which should be followed by a motion-active event of M in the living room. However, as the motion-active event of M becomes an faulty/fake event, the user activity E2E correlation $\langle E_{open}^{contact(\mathsf{C})} \rightarrow E_{detect}^{motion(\mathsf{M})}\rangle$ is violated and an anomaly is detected.

Detection 2. When a resident leaves home, the motion sensor M in the living room is detected, and the contact sensor M attached to the front door must be detected immediately. Then, the front door is expected to be closed. However, as a malfunction occurs in which the event is lost or intercepted, it violates the correlation $\langle E_{detect}^{motion(M)} \wedge E_{open}^{contact(C)} \rightarrow E_{closed}^{contact(C)}\rangle$, and an anomaly is detected.

Detection 3. The smart plug P shall be off when the illumination sensor in MS exceeds a certain threshold by automation rules R1 and R2. Conversely, if the illuminance is lower than a certain criterion, the plug P should be on. However, the smart home application changes its behavior by ghost/fake commands. An anomaly is detected in violation of the E2S correlation $\langle E_{low}^{illuminance(\mathsf{MS})} \rightarrow S_{off}^{switch(\mathsf{P})}\rangle$ generated by the automation rule.

Detection 4. The smart plug P should behave appropriately according to automation rules related to the illuminance sensor MS. Due to command failure (cyber)/command interception, power supply to the smart plug is temporarily cut off. Consequently, the E2S correlation $\langle E_{low}^{illuminance(\mathsf{MS})} \rightarrow S_{off}^{switch(\mathsf{P})}\rangle$ is violated, resulting in the omission of all instances in this case.

Detection 5. Due to the blackout curtain, the illuminance value in the multi-function sensor MS is detected as low or zero. Thus, E2S correlations related to the illuminance events are detected as violation (anomalies A5). But, 6 instances are missing because the living room is brightened by natural light when anomalies occurr. In additon, as appliances connected to the smart plug P are broken (simulated by physically unplugging power cables), there is no operation at all on the plug. Therefore, events associated with A6 are detected as malfunction.

For Detection 1, 3, and 5, some instances are missing, which should be attributed to the incompleteness of the simulations injecting malfunctions. For example, six instances in Detection 1 are missing because fake motion-active events of M are injected during the time when real motion sensors (M) are logged as event logs. Similarly, two missed instances of Detection 3 are resulted from manipulating the smart plug P with a bogus application that is not allowed for the smart home application. Although malfunction is detected, there is a delay time until it is recorded in the event log because they are randomly manipulated operation states. For example, IoT devices turn on or off themselves by random bogus commands. However, there were cases in which the immediately preceding state of off is recorded although a device is on. In Detection 5, six instances are missing because the living room is brightened by natural light when anomalies occur.

TABLE VI. Anomaly Detection Results of Two Methods

Anomaly Index	Correlation-only (COD)		IMEO	
	Precision	Recall	Precision	Recall
A1	98.36 %	95.6 %	98.97 %	94.12 %
A2	91.11 %	82.79 %	100 %	100 %
A3	100 %	100 %	97.02 %	98 %
A4	100 %	100 %	100 %	100 %
A5	100 %	66.67 %	100 %	80 %
A6	100 %	100 %	100 %	100 %

TABLE VII. Comparison of Overall Performance

Method	Precision	Recall	F1 score	Accuracy
IMEO	99.33%	95.35%	0.97	99.98%
COD	97.83%	94.12%	0.95	99.32%

C. Performance Comparison

As summarized in Table VI, IMEO achieves better performance in 5 types. In A2 (faulty and fake events), especially, precision and recall increase from 91.11% and 82.79% to 100% in both. And recall in A5 (physical command failures) increases from 66.67% to 80%. COD can detect E2E, E2S correlation violations in smart home applications, but 17.22% events are lost for anomalies with event interception. In A3 (bogus and fake commands), however, there are small performance degradation.

Table VII compares overall performance of anomaly detection with two methods. IMEO has an average detection precision of 99.33% and a recall of 95.35% across 6 different types of anomaly events, while COD has 97.83% and 94.12%, respectively. It is noted that two methods show similar results in accuracy: 99.98% with IMEO and 99.32% with COD. However, IMEO performs better than COD with respect to the F1 score. This implies that IMEO is able to detect anomalies well even in a real-world smart home environment where malfunctions and/or attacks could occur rarely.

D. Fast Anomaly Detection

We believe that it is critical to reduce anomaly detection time using correlation data for increasing the security of smart home automation. Once detecting an anomaly, in this sense, IMEO memorizes a detection record as described in Section VI-C. When the same malfunction occurs later, it can immediately determine if the event is abnormal by searching for the record history. On the other hand, if the future malfunction is not the same as the history, additional comparisons are made in IMEO, which is likely to take more time. Thus, our experimentation study also measures how long it takes to detect anomalies when using the baseline method and the proposed method. As compared in Table VIII, IMEO takes 1,666 seconds while COD takes 2,647 seconds on average. This shows that the fast anomaly detection process in IMEO can improve performance by 58.9%.

TABLE VIII. Processing Time to Detect Anomalies

	Correlation only (COD)	IMEO
Processing time	44m 07s	27m 46s

IX. Conclusion and Discussion

As IoT devices are integrated and combined with the physical environment, anomalies in them can have serious consequences in our daily lives. Previous solutions that only used a data mining technology to detect anomalies have been struggling with high rates of false alarms and missing many actual anomalies. It also takes a long time to detect anomalies even if they correctly detect anomalies. To overcome the limitations, this paper proposed an anomaly detection system, named IoT Malfunction Extraction Observer, that made use of semantic information at smart homes such as smart home applications, configurations, device types, and installation locations. IMEO used event logs to detect malfunctions to take advantage of semantic information from different channels (smart home applications, physical activities, and user activities). It also provided an easier and faster way to detect frequently repeated malfunctions. These allowed for more reliable malfunction detection. We developed and deloyed the proposed method in a real-world testbed. Experiments were conducted with various abnormal instances, and the results demonstrated that the proposed method achieved higher performance of detection accuracy with faster processing time.

A. Discussion

The evaluation results are very promising, but we consider IMEO as the first step in the anomaly detection using semantic information in smart homes. IMEO has some limitations that we are trying to address in the future.

First, correlations due to user activity channels are useful for detecting anomalies, but false events can occur if there is a deviation in user activity. Such cases rarely occur, but we found them during evaluation. Some events generated events that were irrelevant to the correlation when a user encountered an abnormal situation (e.g., a state with an open front door). One day, for instance, a person wants to read in his or her living room, so he or she turns on the extra light, not the living room light, to increase the illumination. If this rarely happens during the experiments, malfunctions can occur. The key question is how to constantly update correlations to adapt to changes in IoT devices and user activities.

Next, IMEO can only compare and experiment with correlations that result in forward and backward events within a short interval. Correlations that require long intervals, such as the relationship between turning on the air conditioner and temperature events, cannot be detected yet.

Third, the physical constraints of IoT devices are problems to be solved. For example, some IoT devices may be placed relatively far away, and physical channel correlations between them may be very small. One way to solve this problem is to explore the correlations across the entire home rather than separate rooms, which will lead to more correlations between IoT devices. The opposite can also be considered. Recently, the size of houses has decreased, and more and more IoT devices are being installed in the houses. In this case, the redundancy of the correlations can be strong and this information needs to be interpreted differently.

Last, an attacker who knows correlation, that is, semantic-based detection, can construct an attack that does not violate correlation to avoid detection. The study of robustness to this type of attack will be an interesting topic. The key to IMEO execution is that it imposes additional constraints on the attacker. In the correlation channel, each attribute is included in at least four correlations. Attacking the device without violating the correlation is a barrier for the attacker.

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Cross-Modal Sentiment Analysis Based on CLIP Image-Text Attention Interaction

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***Abstract*—Multimodal sentiment analysis is a traditional text-based sentiment analysis technique. However, the field of multi-modal sentiment analysis still faces challenges such as inconsistent cross-modal feature information, poor interaction capabilities, and insufficient feature fusion. To address these issues, this paper proposes a cross-modal sentiment model based on CLIP image-text attention interaction. The model utilizes pre-trained ResNet50 and RoBERTa to extract primary image-text features. After contrastive learning with the CLIP model, it employs a multi-head attention mechanism for cross-modal feature interaction to enhance information exchange between different modalities. Subsequently, a cross-modal gating module is used to fuse feature networks, combining features at different levels while controlling feature weights. The final output is fed into a fully connected layer for sentiment recognition. Comparative experiments are conducted on the publicly available datasets MSVA-Single and MSVA-Multiple. The experimental results demonstrate that our model achieved accuracy rates of 75.38% and 73.95% , and F1-scores of 75.21% and 73.83% on the mentioned datasets, respectively. This indicates that the proposed approach exhibits higher generalization and robustness compared to existing sentiment analysis models.**

Keywords*—*Multi-modal; image-text interaction; multi-head attention mechanism; sentiment analysis; cross-modal fusion

I. Introduction

2023 Global Digital Report [1] indicates that there are currently 5.16 billion internet users and 4.76 billion social media users worldwide, accounting for 59.4% of the global population. The global social media user base has grown by 3.0% year-on-year, equivalent to 137 million people. With the continuous flourishing development of social networks and internet-enabled mobile devices, there is a growing diversity of expressions for emotions or opinions on various topics posted on social media and various website platforms. This evolution has transitioned from initial text information to gradually include multimodal information such as images, audio, and videos. Consequently, utilizing multimodal feature information for sentiment analysis has become one of the research hotspots in recent years [2], and it has been successfully applied in various potential applications, including decision-making [3], personalized advertising [4], emotion retrieval [5][6], and other domains.

Early sentiment analysis (SA) models mainly focused on text, and manual features were usually designed using limited human knowledge. Text features can quickly summarize subjective emotions, but cannot fully describe the highly abstract nature of emotions. For single-modal approaches, extreme cases such as irony often posed challenges in meeting sentiment analysis needs. In recent years, the rise of deep learning has provided powerful tools for Multimodal Sentiment Analysis (MSA). MSA leverages massive multimodal data generated on social media for integrated analysis, combining various multimodal features. This approach not only enables a more comprehensive understanding of user emotional expressions but also effectively addresses limitations of single-modal methods in handling complex emotions, ambiguity, or extreme cases like irony [7].

However, there are still some shortcomings in multimodal feature fusion methods. In early multimodal fusion methods, they either simply concatenate the extracted multimodal features [8] or roughly integrate relationships between images and text on a horizontal feature level [9] to obtain concatenated or linearly fused feature representations. These methods lack in-depth exploration of the complex relationships between multiple modal features. On the other hand, information loss, redundancy, and noise among different modal features can affect sentiment judgments. Effectively utilizing the complex correlations between high-level abstract features and low-level abstract features across modalities and improving method fusion effectiveness pose significant challenges in the field of multimodal analysis [10].

In order to solve the problem of multi-modal model fusion, this paper proposes a Multimodal Sentiment Analysis model, named CLIP-CA-CG, based on Contrastive Language-Image Pretraining (CLIP) [11], cross-attention, and cross-modal gating.The CLIP model maps text and images into a shared embedding space, making related text descriptions and image representations in this space closer, modeling at fine-grained features, and the model uses contrastive learning and pre-training. This method can learn feature representations with good generalization capabilities and reduce computational pressure and speed. Additionally, considering the complementary role of the contextual information of image text in sentiment analysis, where the same word may cause different emotions in different contexts, so this model integrates the original cross-modal feature information through the self-attention mechanism. This can extract high-level abstract features while maximizing the fusion of environmental features, which helps the model learn the correlation between different modalities to more comprehensively explore multi-modal emotions.

The remainder of the paper is structured as follows: Section II will review related research on sentiment analysis of unimodal and multimodal models, Section III will provide the methods proposed in this study, Section IV will introduce the experimental analysis and discussion, and finally, conclusion and future works are provided on Section V.

II. Related Work

A. Single-modal Sentiment Analysis

1) Text sentiment analysis: In the past, conventional techniques for text sentiment analysis primarily utilized dictionary methods [12]. In this approach, the sentiment scores of individual words within the text are combined based on predefined values. Text sentiment classification methods can be roughly divided into two categories, namely dictionary based models and machine learning models. Hu et al. [13] predicted the semantic analysis orientation of opinion sentences by using adjectives as prior positive or negative polarity. Taboada et al. [14] introduce a dictionary-based method called the Semantic Orientation Calculator (SO-CAL), which not only utilizes word dictionaries annotated with semantic orientations but also incorporates reinforcement and negation factors. Barbosa et al. [15] proposed a two-step sentiment classification method for Twitter messages using online tags as training data.

With the evolution of machine learning, Pang et al. [16] are the first to introduce machine learning methods into text sentiment classification, including Naive Bayes (NB) [17], Support Vector Machine (SVM) [18], and Maximum Entropy Classifier. However, machine learning performance heavily relies on the quality and quantity of the training set. Inspired by the success in the field of Natural Language Processing (NLP), Kim et al. [19] first apply Convolutional Neural Networks (CNN) in text sentiment classification. Tai et al. [20] considered the complex structure of text features and introduced Tree LSTM for sentence sentiment classification. Tang et al. [17] first combined CNN and LSTM to obtain text sentence representations, and then used recursive neural networks to encode their intrinsic connections [21]. Researchers also adopt various neural network models for sentiment analysis, such as hierarchical attention network model (HAN) to select important feature information [22] and facial expression recognition network based on enhanced attention [23].

As large models gain prominence, word embeddings and pre-trained models have seen significant success in sentiment analysis. Word2Vec [24] maps semantically similar words to similar vector spaces, while GloVe [25] derives semantic relationships between words based on global co-occurrence. ELMo [26] introduces context-aware embeddings, allowing word representations to vary based on their specific contexts within sentences. The emergence of BERT [27] further propels the development of sentiment analysis. Built on self-attention mechanisms, BERT captures long-range dependencies and contextual information more effectively. This context-sensitive representation enables BERT to achieve outstanding performance in sentiment analysis tasks, particularly excelling in handling complex sentence structures and context-dependent sentiment expressions.

2) Visual sentiment analysis: Visual sentiment analysis has undergone significant development. In the early stages, image sentiment analysis involved inferring emotions from low-level features. For example, Machajdik et al. [28] predict emotions by extracting features such as texture and color. Borth et al. [29] used the SentiBank model to identify adjective noun pairs (ANP) and extract visual semantic information.Yuan et al. [30] proposed an image sentiment method that utilizes 102 intermediate visual attributes to make the classification results more interpretable.

In recent years, with the continuous advancement of deep learning, researchers have explored the coordination of image color and content in relation to emotional expression. Yang et al. [31] developed a multi task framework to optimize visual emotion models by considering mixed images of multiple emotions. Ruan et al. [32], for instance, employ CNN networks to extract both content and color features from images. By introducing attention mechanisms and sequence convolution, they adeptly model the correlations between content and color features. To delve deeper into the semantic associations among visual emotion regions, Zhang et al. [33] utilize a fully convolutional neural network for image saliency detection. The CNN selection strategy is employed for filtering, and ultimately, Transformer encoders [34] are used to analyze the correlations between different emotion regions, thereby obtaining a comprehensive emotional output.

B. Multimodal Sentiment Analysis

In the field of multimodal research, psychologists have confirmed that emotions are primarily influenced by the joint effects of multimodal data, with visual-text emotional features being particularly prominent. The same piece of text pairs with different images may elicit completely opposite emotions. In early multimodal sentiment analysis, researchers concatenate, added, or weighted shallow features. Cao et al. [35], for example, analyze cross-media sentiment analysis through visual and textual methods. Yu et al. [36] use a pre-trained CNN model to extract feature representations and ultimately fused textual features for sentiment classification.Zhao et al. [37] proposed an image text consistency driven method that utilizes text features, social features, low-level and intermediate visual features, and image text similarity.

As deep learning continues to evolve, mid-term model fusion and late-stage decision fusion methods are showing remarkable success. Yang et al. [38] achieve good results by stacking and gradually pairing different feature vectors on datasets like CMU-MOSI. Poria et al. [39] detail an approach using Long Short-Term Memory (LSTM) networks to capture interdependencies and relationships between utterances in multimodal sentiment prediction. Huang et al. [40] proposed a Deep Multimodal Attention Fusion (DMAF) method, which utilizes both intermediate and post fusion, combining unimodal features and internal cross modal correlations to improve accuracy. Liu et al. [41] introduce a shared memory attention mechanism, capturing interactions between two modalities and their impact on sentiment using similar features.

In recent years, multimodal tasks have made significant progress, benefiting from the latest developments in visual language models. Cheema et al. [42] apply CLIP in multimodal sentiment analysis, demonstrating its potential as a powerful baseline for emotion prediction tasks in tweets. Arevalo et al. [43] propose the Gated Multimodal Unit (GMU) model, which controls the influence of input modalities on unit activation levels for data fusion. Gupta et al. [44] introduce a Collaborative Attention Model based on RoBERTa and FiLMed ResNet, addressing the issue of visual-text inconsistency through joint attention mechanisms.

Although multi-modality has made certain progress in emotional tasks, there is still much room for improvement in image-text feature interaction. Most existing methods simply connect features extracted from different modalities, or simply learn The relationship between images and text leads to bias in complex tasks. Considering the complex relationship between the two modalities and the efficiency of the model, we use a pre-trained model to extract feature networks while capturing the potential alignment between image regions and text words, and finally consider the complementary role of individual modalities in emotion prediction. , situational features are also integrated into our network.

III. Methods

This paper proposes a cross-modal sentiment model, CLIP-CA-CG, based on CLIP image-text attention interaction, as illustrated in Fig. 1. The model architecture consists mainly of a feature extraction layer, an interaction attention layer, a gating fusion layer, and a regression layer. The feature extraction module utilizes existing methods for extracting features from images and text, producing feature vectors for each and a fused feature vector. The interaction attention module enhances the feature representation of images and text based on a multi-head attention mechanism, further exploring consistent emotional features in the image-text pairs. The gating fusion module aligns high-level abstract image-text features, fuses global concrete features, and introduces an adaptive cross-selective block to determine how much interaction information each component should transmit. Finally, sentiment is comprehensively predicted through a multi-layer perceptron and a Softmax regression layer.

A. Image-Text Feature Extraction

The original input of the model consists of two modalities: text and image. For the raw textual data, a set of textual data T can be represented as n words forming $T = [T_1, T_2, ..., T_n]$, where n represents the maximum length of the sequence. Considering the need for a more comprehensive understanding of context and capturing bidirectional language relationships, this paper utilizes the pre-trained RoBERTa (Robustly optimized BERT approach) model to encode the text sequence T. The advantage of the RoBERTa model lies in further optimizing the BERT model by adjusting training tasks, datasets, learning rates, etc. Additionally, unlike BERT, RoBERTa does not add special token embeddings at the beginning and end of the input text, enhancing the generalization of text feature extraction. The textual data is embedded into vectors $F_{T-RoBERTa}$ by the RoBERTa model, where each word is represented in the vector space.

$$F_{T-RoBERTa} = [f_1, f_2, ..., f_x, ..., f_N] \subseteq R^{d \times N} \tag{1}$$

In the equation: f_x represents the contextual semantic feature of the x-th word, d is the output dimension of the RoBERTa model (768), and N is the maximum length of the RoBERTa model's word encoding.

Then, to summarize the contextual information in the sentence, a Bidirectional Gated Recurrent Unit (Bi-GRU) [45] is employed. The combination of RoBERTa and Bi-GRU ensures the learning of text semantics while preserving multi-granular, multi-level information extraction from the text. The vector $F_{T-RoBERTa}$ is passed through the Bi-GRU gated units to further extract and generate the feature h_x.

$$h_x = [\overrightarrow{GRU}(f_x) \oplus \overleftarrow{GRU}(f_x)] \subseteq R^d \tag{2}$$

In the equation: h_x is the feature extracted from f_x through Bi-GRU, $\overrightarrow{GRU}(f_x)$ denotes obtaining the forward hidden state information, and $\overleftarrow{GRU}(f_x)$ represents acquiring the backward hidden state information. Finally, the average of the bidirectional hidden state information, h_x, is obtained, yielding the ultimate textual semantic feature F_T.

$$F_T = [h_1, h_2, ..., h_N] \in R^{d \times N} \tag{3}$$

For image features, ResNet introduces a residual network structure, addressing the issue of gradient vanishing that arises with increasing network depth. Moreover, deeper network structures can handle images under different sizes, angles, and lighting conditions. In this paper, pre-trained ResNet50 is used for feature extraction. Simultaneously, each original image is cropped to 224×224×3 as input for ResNet50. After convolution and pooling, the image feature F_{In} is obtained. Finally, aligning visual feature F_{In} and textual feature FT through a perceptron results in the ultimate image feature F_I.

$$F_I = Linear(F_{In}) \tag{4}$$

After obtaining the original visual and textual features, this paper further utilizes Contrastive Language-Image Pre-training (CLIP) to integrate image and text features, thereby establishing a close connection between them. The core idea of CLIP involves using contrastive learning to represent images and text in a shared embedding space. It maximizes the cosine similarity of paired image and text embeddings while minimizing the cosine similarity of unpaired image and text embeddings. This ultimately brings related images and text closer in this shared space. The original visual-text features, after passing through the CLIP model, result in the fused feature F_{IT}.

$$F_{IT} = CLIP(F_I) \odot CLIP(F_T) \tag{5}$$

B. Multi-Head Attention Mechanism

Multi-Head Attention (MHA) is an extended form of the self-attention mechanism initially introduced in the Transformer model. The core idea is to use multiple distinct attention heads, allowing the model to learn various attention patterns in parallel, with each head focusing on different parts of the sequence. Subsequently, by concatenating the outputs of these heads and projecting them through a linear layer, the final output of multi-head attention is generated. The input to the self-attention mechanism consists of key vectors, query vectors, and value vectors. The mechanism calculates the similarity between query and key vectors, applies a Softmax operation to obtain attention weights for weighted summation, resulting in the final self-attention output as expressed in Formula (6).

$$Attention(Q, K, V) = Softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{6}$$

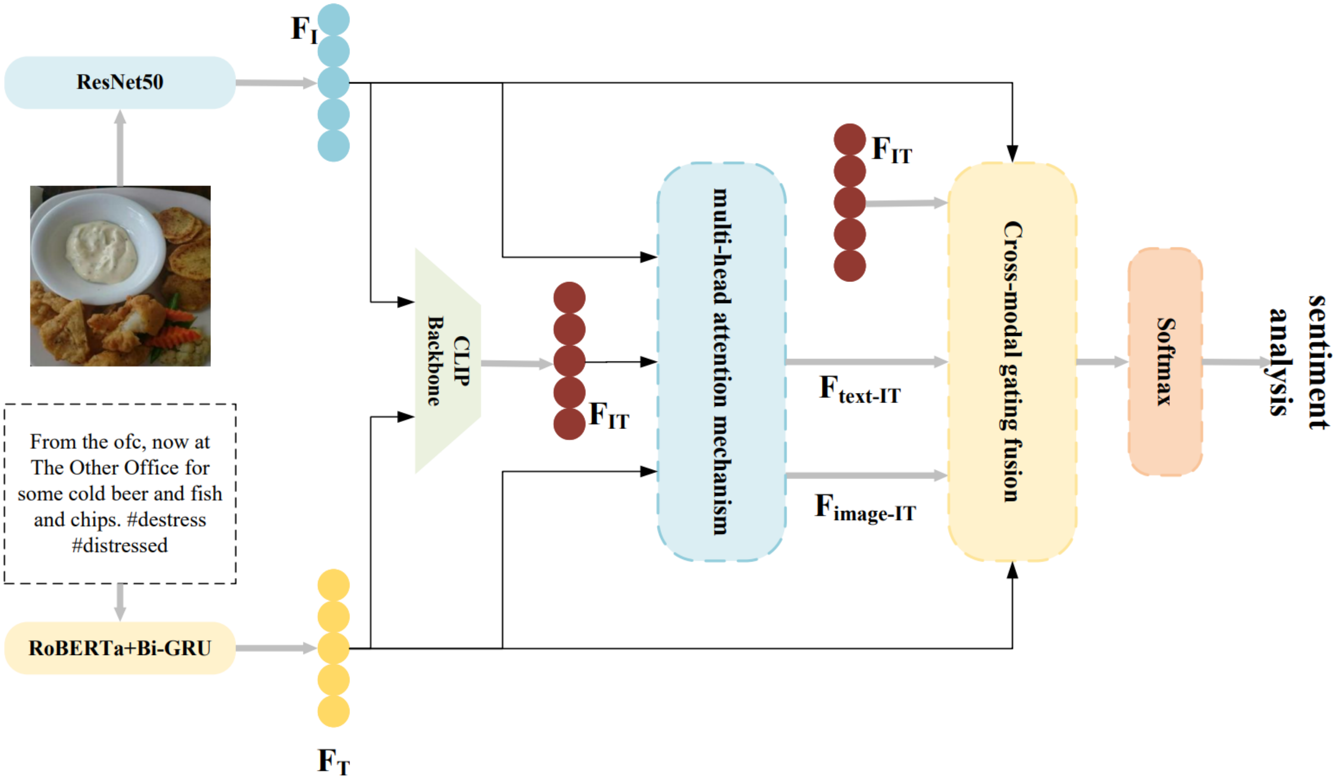
ResNet50
F_I
From the ofc, now at The Other Office for some cold beer and fish and chips. #destress #distressed
RoBERTa+Bi-GRU
F_T
CLIP Backbone
F_{IT}
multi-head attention mechanism
F_{IT}
$F_{text-IT}$
$F_{image-IT}$
Cross-modal gating fusion
Softmax
sentiment analysis

Fig. 1. Overall architecture diagram of the model.

In the equation: Q represents the query matrix, K represents the key matrix, V represents the value matrix, and dk is the dimensionality of the query vectors. Multi-Head Attention is an operation that stacks multiple self-attention mechanisms to focus on different representations of information at different positions.

$$MHA(Q, K, V) = Concat(head_1, ..., head_h)W^O \tag{7}$$

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V) \tag{8}$$

In the equation: $head_i$ represents the calculation of the i-th attention head, W_i^Q, W_i^K,W_i^V are the weight matrices for linear mappings, and W^O is the weight matrix for the linear mapping of the output. Multi-Head Attention typically includes h attention heads, each with independent weights. The schematic diagram of the multi-head attention mechanism used in this paper is shown in Fig. 2.

By utilizing the image-text features from CLIP, we can obtain more comprehensive global information. In this study, we choose the fusion feature F_{IT} as the main modality for multi-head attention, while visual feature F_I and text feature F_T serve as secondary modality inputs. The main modality learns the sequential information of the secondary modality and ultimately improves the convergence speed and expressive capability of the model through forward propagation. The final output yields feature vectors $F_{image-IT}$ and $F_{text-IT}$.

$$F_{image-IT} = LayerNorm(F_I + MHA(Q_I, K, V)) \tag{9}$$

$$F_{text-IT} = LayerNorm(F_T + MHA(Q_T, K, V)) \tag{10}$$

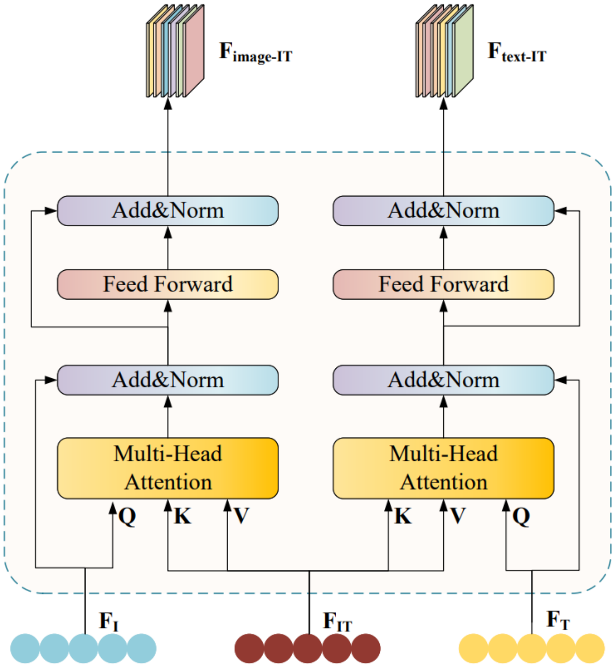

Fig. 2. Principle diagram of multi-head attention mechanism.

C. Cross-modal Gating Fusion

The cross-modal joint feature vector is generated through the interaction and fusion of features from two modalities. It allows vector features to pass fragmentary messages across both modalities for cross-modal interaction. However, in practice, there are still issues such as information redundancy, loss, noise, and region misalignment. To overcome these drawbacks and fully utilize the complementary information of modality correlations contained in the joint features, this paper further proposes a cross-modal gating fusion module. This module adaptively controls the fusion strength through model training to obtain multi-modal fusion features by concatenating them. Considering the significant role of environmental information in sentiment analysis, where the same object may evoke different emotions in various text or visual contexts, it is essential to supplement the fusion with the original image and text features. The structure of the cross-modal gating fusion is illustrated in Fig. 3.

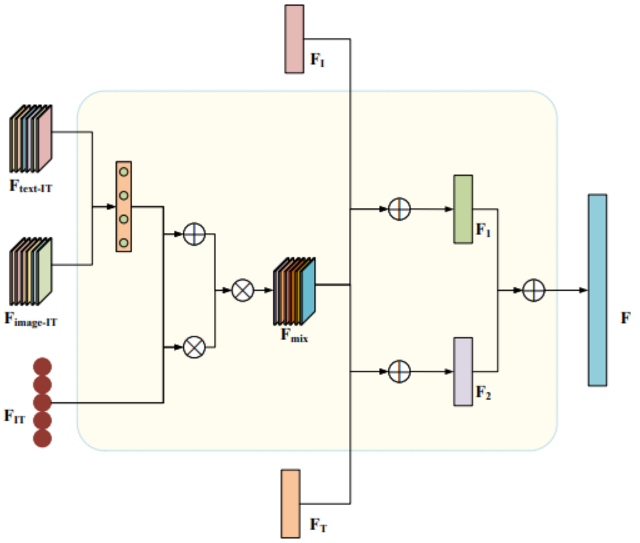

Fig. 3. Cross-modal gated fusion structure diagram.

Firstly, the feature vectors $F_{image-IT}$ and $F_{text-IT}$ obtained through multi-head attention are concatenated to achieve the weight adjustment of joint features. This preserves effectively correlated information in the features, ultimately obtaining the complementary information feature FVT from both, as shown in Formula (11).

$$F_{VT} = [F_{image-IT}, F_{text-IT}] \quad (11)$$

To balance obtaining superior global feature information and the output from higher layers, the output obtained from the features F_{VT} and the globally extracted features F_{IT} by CLIP are used as inputs for fusion. After concatenation and non-linear transformation, the final mixed visual-textual feature information F_{mix} is obtained.

$$F_{mix} = \sigma(Concat(F_{IT}, F_{VT}), Norm(F_{IT}, F_{VT})) \quad (12)$$

In the equation, the σ function represents the fusion of concatenated visual-textual features and non-linearly transformed visual-textual features through trainable parameters. Finally, considering the complementary role of contextual information, we combine the single-modal contextual information feature with the mixed feature F_{mix}, and ultimately generate the final feature F through an MLP.

$$F_1 = MLP(F_I \oplus F_{mix}) \quad (13)$$

$$F_2 = MLP(F_T \oplus F_{mix}) \quad (14)$$

$$F = \lambda F_1 + (1 - \lambda) F_2 \quad (15)$$

In the equation, λ represents the concatenation operation, which is used to control the balance between aggregating visual and textual features.

D. Multimodal Sentiment Classification

The ultimate goal of sentiment analysis is to accurately classify the emotions expressed in multimodal data, such as Positive, Neutral, Negative, etc. To achieve this, the multimodal fusion feature F obtained through the multi-head attention and fusion module is fed into a fully connected layer and a Softmax layer, ultimately producing a probability distribution y for possible sentiment labels.

$$y = Softmax(Linear(F)) \quad (16)$$

In the equation: The Linear network represents the fully connected layer, and the classification results are obtained through Softmax. For model training, this paper utilizes the Adam optimizer to train the model, minimizing the cross-entropy loss.

IV. Experimental Analysis

A. Datasets

In this study, to validate the sentiment analysis performance of the CLIP-CA-CG model, we utilize two publicly available datasets, MVSA-Single and MVSA-Multi, established by Niu et al. [46]. These datasets are collected from the popular social media platform Twitter. The MVSA-Single dataset comprises 5129 pairs of images and text, while the MVSA-Multi dataset includes 196,000 pairs of images and text. The MVSA project provides standardized benchmarks, representing a significant development in the multimodal domain. The data is labeled with sentiment polarity, including positive, neutral, and negative emotions.

For a fair comparative study, we conduct preprocessing on both datasets. During this process, we remove cases where there is emotional inconsistency between the image and text labels, such as one label being positive (or negative) while the other is neutral. Such cases are considered as having a positive (or negative) sentiment label. The resulting new datasets are denoted as the revised MVSA-Single dataset and revised MVSA-Multi dataset, as shown in Table I.

TABLE I. MVSA-Single and MVSA-Multi Datasets

Dataset	Positive	Neutral	Negative	Total
MSVA-Single	2683	470	1358	4511
MSVA-Multiple	11318	4408	1298	17024

B. Implementation Details

In the experiments, we randomly divide the new datasets into training, validation, and test sets, with a data split ratio of 8:1:1. Regarding the experimental environment and parameters, the proposed model is implemented using Python 3.7, developed in the PyTorch 1.9.0 framework, and executed on CUDA 12.0. To eliminate external influences, all experiments are conducted on a server with 64GB of memory and an NVIDIA GeForce RTX 4090 GPU.

In terms of hyperparameter configuration for the model, this experiment employs the cross-entropy loss function and mean squared error loss function for computing the loss of classification and regression tasks, respectively. Adam is utilized as the optimizer for the CLIP-CA-CG model, initialized with a learning rate of 0.0001, executed over 100 epochs, with a 10-fold reduction in learning rate every 10 epochs, and a weight decay of 1e-5. For visual encoding,we utilize the pre-trained ResNet50 to extract image features, taking as input pre-processed image information in the form of a 224×224×3 matrix. In text encoding, we employ pre-trained RoBERTa for extracting text features, where the dimensionality of the extracted word vectors is 768, and subsequently align them for input into the model network. Given the disparate sample sizes in the two datasets, the batch size is set to 64 for the MVSA-Single dataset and 128 for the MVSA-Multi dataset. The initial hyperparameter settings are configured as shown in Table II.

TABLE II. Experimental Parameter Environment

Parameter	Value
Batch_size	64 / 128
Learning_rate	0.0001
Optimizer	Adam
Dropout	0.3
Epochs	100
Text_dimension	768

Finally, to validate the model's effectiveness, comparative experiments are conducted, wherein the proposed model is compared with other mainstream single-modal and multi-modal fusion experiments. Performance evaluation metrics include accuracy and $F_{1-score}$ (F1), calculated as follows.

$$P = \frac{T_P}{T_P + F_P} \tag{17}$$

$$R = \frac{T_P}{T_P + F_N} \tag{18}$$

$$F_1 = \frac{2 \times P \times R}{P + R} \tag{19}$$

$$Acc = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{20}$$

In the equation: T_P represents true positive, T_N represents true negative, F_P represents false positive, F_N represents false negative, P represents precision, and R represents recall.

C. Model Comparison Experiment

In this study, we compare the proposed model with the following benchmark models in terms of accuracy and F1 score. SentiBank and SentiStrength [47] models rely solely on traditional statistical features and are unable to effectively extract key intrinsic features from both images and text, resulting in lower accuracy. Compared to other models, CNN-Multi [48] extracts text and image features separately using two individual CNNs. Benefiting from the powerful feature extraction capability of deep neural networks, this enhances the expressiveness of emotions, and the final prediction is made by connecting these features. The DNN-LR model [49] adopts transfer learning by using pretrained models and utilizes logistic regression for decision analysis. The Co-Memory model [9], introducing a fusion module in sentiment analysis, promotes feature connections between modalities. The MVAN model [38] enhances the semantic image-text features by employing a memory network module on the basis of a multi-view attention network, further improving dataset accuracy. The CLMLF model [50] utilizes contrastive learning to enhance the representation capability of image-text features, fostering relationships between images and text, thus improving model accuracy. The ITIN model [51] introduces cross-modal alignment operations and an adaptive cross-modal gate fusion module, significantly improving accuracy in sentiment analysis tasks.

TABLE III. Comparative Experiments of Several Models

Model	MVSA-S		MVSA-M	
	Accuracy (%)	F1 (%)	Accuracy (%)	F1 (%)
SentiBank&SentiStrength	52.05	50.08	65.62	55.36
CNN-Multi	61.20	58.35	66.39	64.19
DNN-LR	61.42	61.03	67.86	66.33
Co-Memory	70.51	70.01	69.92	69.83
MVAN	72.98	72.98	72.36	72.30
CLMLF	75.33	73.46	72.00	69.83
ITIN	75.19	74.97	73.52	73.49
CLIP-CA-CG (Ours)	**75.38**	**75.21**	**73.95**	**73.83**

As indicated in Table III, the proposed CLIP-CA-CG model achieves the best performance compared to other benchmark models on both the MVSA-S and MVSA-M datasets. This suggests that our model can effectively exploit the correlations between different modalities. Additionally, by preprocessing the model, we can effectively reduce the difficulty of model training. Finally, the model considers the adjustment of weights based on joint features between modalities and environmental features, thus achieving more accurate sentiment classification.

Compared to the SentiBank and SentiStrength models, both SentiBank and SentiStrength models exhibit inferior overall performance. This is attributed to the conventional feature statistics often failing to comprehensively encapsulate the intrinsic features of multimodal information, leading to missing or erroneous feature information inputted into the model, consequently resulting in inaccurate model predictions.

The CNN-Multi, DNN-LR, and Co-Memory models all utilize deep learning for feature extraction, which facilitates the extraction of data features. It is noteworthy that the Co-Memory model introduces a fusion module into sentiment analysis, resulting in a significant improvement in model accuracy. This suggests that effectively integrating image and text features is a viable approach for enhancing the accuracy of multimodal sentiment analysis. Although this approach can learn invariant or specific representations across multiple modalities, it also brings about issues such as excessively redundant feature representations, thereby affecting the effectiveness of fused features.

The MVAN, CLMLF, and ITIN models all incorporate attention mechanisms, which, as observed from the results, further enhance model performance. This indicates that attention mechanisms can focus on more valuable and contributory features. Additionally, considering issues such as feature fusion across modalities and feature redundancy, methods such as contrastive learning and adaptive cross-modal gating fusion have also, to some extent, improved model performance.

Building upon the strengths and weaknesses of baseline models, the proposed CLIP-CA-CG model first enhances the representation capability of image-text data by leveraging pre-trained vision and language models along with contrastive learning techniques. Concurrently, it incorporates a multi-head attention mechanism to capture and express image-text features at a finer granularity. Finally, by exploiting the interaction between images and text, the model utilizes a fusion interaction module to extract both global and focal features of image-text features. These features are complemented with environmental features for more accurate sentiment prediction. Experimental results demonstrate superior performance across public datasets.

D. Ablation Experiment

To validate the performance improvement of each module in multimodal sentiment analysis, we conduct a series of experiments focusing on image and text feature extraction methods, feature fusion methods, etc., to verify the effectiveness of the CLIP-CA-CG model. The details of the model ablation experiments are explained below.

- V_{only} and T_{only}: Represent the evaluation of sentiment analysis using only the visual modality and only the text modality, respectively.
- CLIP-CA-CG w/o Clip: Remove the Clip image-text contrastive model from the complete model, eliminate further feature extraction and fusion, and directly input the preliminary extracted image features and text features into the multi-head attention module.
- CLIP-CA-CG w/o CA: Remove the multi-head attention mechanism from the complete model, and directly input the obtained joint features along with the image and text features into the fusion module.
- CLIP-CA-CG w/o CG: Remove the cross-modal interaction fusion module from the complete model. Instead, use a simple concatenation method to combine multimodal data and process the fused features with an encoder.

TABLE IV. Ablation Experiments on MSVA-Single Dataset

Model	**Accuracy (%)**	**F1 (%)**
V_only	63.04	62.76
T_only	71.87	71.19
CLIP-CA-CG w/o Clip	73.65	73.36
CLIP-CA-CG w/o CA	72.15	71.56
CLIP-CA-CG w/o CG	72.41	71.98
CLIP-CA-CG (Ours)	**75.38**	**75.21**

According to the experimental settings, we conduct ablation experiments on the MSVA-Single dataset. As shown in Table IV, proposed CLIP-CA-CG model performs the best, and the absence of any modality or module results in a decrease in model performance. The V_{only} and T_{only} models, which extract features and make sentiment judgments using only a single modality, have the lowest accuracy compared to other experiments. The accuracy of the text model is 71.87, while the accuracy of the image model is only 63.04. This indicates that in the field of sentiment analysis, text has a stronger expressive capability than images. Additionally, incorporating multimodal features can complement information, improving the performance of sentiment analysis models. This provides a solid foundation for subsequent multimodal fusion experiments.

CLIP-CA-CG w/o Clip, CLIP-CA-CG w/o CA, and CLIP-CA-CG w/o CG models respectively remove the Clip contrastive learning module, the multi-head interaction attention module, and the gate fusion module. The experimental results show that the removal of these three modules led to varying degrees of performance degradation in all evaluation metrics. This indicates that these three modules have a promoting effect on the proposed CLIP-CA-CG model.

Specifically, the CLIP-CA-CG w/o Clip model, lacking the utilization of the CLIP pre-trained model, suffers from partial information interaction loss in the early feature extraction, affecting the model's feature fusion to some extent. The CLIP-CA-CG w/o CA model, due to the removal of the attention mechanism, hinders the effective capture of complex relationships between images and text. It fails to extract information components between modalities, making it challenging to ensure the model's robustness at a fine-grained level. The CLIP-CA-CG w/o CG model, obtaining fusion features through direct concatenation, often experiences information loss, redundancy, and noise, leading to a reduction in model accuracy.

V. Conclusion

Addressing the challenges of insufficient inter-modal information, information redundancy, and low effectiveness of fused features in existing multi-modal sentiment analysis, this paper proposes a cross-modal sentiment model, CLIP-CA-CG. The paper first elaborates on the overall architecture of the CLIP-CA-CG model. This model utilizes pre-trained RoBERTa and ResNet50 models to extract textual and visual features. Subsequently, the obtained features are further processed through CLIP contrastive learning to acquire deeper-level features. The model then employs multi-head attention mechanisms and cross-modal fusion modules for global feature, fine-grained feature, and contextual feature extraction, ultimately the control feature weights are input to the fully connected layer for sentiment analysis. In the experimental setup, this paper conducts comparative experiments and ablation experiments with several commonly used multi-modal sentiment analysis models on the public datasets MSVA-Single and MSVA-Multiple. The experimental results show that the accuracy of the CLIP-CA-CG model reaches 75.38% and 73.95%, and the F1 score reaches 75.21% and 73.83%, respectively, validating the generalization and robustness of the CLIP-CA-CG model.

The paper also has some limitations. Due to constraints on data resources, we did not further validate the robustness of the model using other publicly available datasets. Additionally, only two modalities, namely image features and text features, were utilized for experimentation, which might lead to misjudgment in complex scenarios. In future research, we intend to incorporate more modalities to form a more sophisticated multi-modal sentiment analysis model, aiming to further improve the accuracy and generalization of sentiment analysis.

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Automation Process for Learning Outcome Predictions

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***Abstract*—This paper presents a comprehensive study on the evaluation of algorithms for automating learning outcome predictions, with a focus on the application of machine learning techniques. We investigate various predictive models (logistic regression, random forest, gaussian naive bayes, k-nearest neighbors and support vector regression) to assess their efficacy in forecasting student performance in educational settings. Our experimental approach involves the application of these models to predict the outcomes of a specific course, analyzing their accuracy and reliability. We also highlight the significance of an automation process in facilitating the practical application of these predictive models. This study highlights the promise of machine learning in advancing educational assessment and paves the way for further investigations into enhancing the adaptability and inclusivity of algorithms in various educational settings.**

Keywords*—Machine learning; predictive learning outcomes; education; logistic regression; k-nearest neighbors; Gaussian Naive Bayes; Random Forest; support vector regression

I. Introduction

In the evolving landscape of educational technology, machine learning (ML) emerges as a pivotal tool, revolutionizing decision-making processes across various domains, particularly in education [1]. The integration of ML in educational settings has led to significant advances, such as personalized learning paths based on student data analysis, automated grading systems, and predictive models for student performance and learning outcomes [2]. These innovations underscore the transformative potential of ML in enhancing educational effectiveness and efficiency.

Despite these advances, the field faces several challenges. The complexity of educational data, characterized by its multidimensionality and the dynamic nature of learning processes, presents a significant hurdle [3]. Traditional ML algorithms often struggle to capture the nuanced patterns of learning, leading to inaccuracies in outcome predictions. Furthermore, the ethical considerations surrounding data privacy and the potential biases in algorithmic decisions add layers of complexity to the deployment of ML in education.

A critical overview of ML algorithms reveals their potential in predicting learning outcomes. These algorithms range from traditional statistical models to advanced deep learning networks, each offering unique perspectives in understanding student performance [2]. The importance of automation in this context cannot be overstated. Automation, in its essence, transforms the labor-intensive and often subjective process of outcome prediction into an objective, efficient, and scalable task [4].

An unsolved problem in this domain is the comprehensive automation of learning outcome predictions. While some progress has been made, existing systems either require significant manual intervention or fail to adapt to the evolving educational landscapes [1]. This gap not only hinders the scalability of ML solutions in education but also limits the potential for real-time, adaptive learning interventions.

The importance of this study lies in its focus on addressing these challenges by proposing an innovative approach to automate learning outcome predictions. By leveraging the latest advancements in deep learning and data analytics, this paper aims to develop a model that can accurately predict learning outcomes across diverse educational settings, thereby facilitating more personalized and effective learning experiences.

The novelty of our work is twofold. First, it introduces a novel algorithmic framework that combines the strengths of deep learning with the insights gained from educational psychology, aiming to better understand and predict learning behaviors. Second, it proposes a scalable automation process that can adapt to different learning environments and student profiles, significantly reducing the need for manual data processing and intervention.

This paper is structured into five sections, each designed to build upon the last in addressing the identified research gap. Following this introduction, we delve into a detailed review of the advances and challenges in ML applications in education, setting the stage for our novel contributions. We then present our methodology, focusing on the design and implementation of our predictive model. This is followed by an analysis of the results, demonstrating the effectiveness and adaptability of our approach. The paper concludes with a discussion of the implications of our findings for the future of ML in education, highlighting potential directions for further research.

II. Predicting Algorithms

A. Logistic Regression

Logistic Regression, a cornerstone in the realm of predictive analytics, offers a robust mathematical framework particularly suited for educational data [5]. Its essence lies in modeling the probability of a binary outcome, making it an ideal candidate for deciphering the dichotomous nature of learning outcomes: success or failure, pass or fail [6].

The application of Logistic Regression in predicting learning outcomes involves a meticulous process of mapping input variables — typically, the learning outcomes of certain subjects

— to a binary output, representing the predicted success or failure in other subjects. In the context of predicting learning outcomes, Logistic Regression is applied by modeling the probability of a student achieving a certain outcome (e.g., passing a subject) based on their performance in other subjects. The model's prowess stems from its ability to handle categorical data, a common characteristic of educational datasets. Logistic Regression shines in its simplicity and interpretability, a crucial aspect when educators and policymakers are at the helm, making decisions based on its predictions [7].

Several studies have illuminated the efficacy of Logistic Regression in educational settings. Singh and Jaiswal explored various machine learning classifiers, including Logistic Regression, in analyzing student performance in virtual learning environments [6]. Similarly, Lin et al. employed Logistic Regression, among other algorithms, to predict student submission timeliness in programming courses, highlighting the algorithm's versatility [8]. In conclusion, Logistic Regression stands out as a versatile and easily interpretable tool, essential for enhancing educational strategies through data analysis.

B. Random Forest

Random Forest, an ensemble learning method renowned for its robustness and accuracy, stands as a paragon in the domain of predictive analytics, particularly in educational settings [9]. At its core, Random Forest builds multiple decision trees and merges them to obtain a more accurate and stable prediction, a method especially effective in handling the multifaceted nature of educational data.

The Random Forest model can be conceptualized [10] as an aggregation of predictions from multiple decision trees, each contributing to the final decision. This ensemble approach significantly reduces the risk of over-fitting, a common pitfall in complex datasets such as educational data. The mechanics of Random Forest are particularly suited for educational data, which often encompasses a mix of categorical and continuous variables. By constructing a 'forest' of decision trees, each analyzing a subset of the data, Random Forest captures complex, non-linear relationships that might elude simpler models [11].

Several studies underscore the efficacy of Random Forest in this realm. Petkovic et al. demonstrated the algorithm's capability in predicting student learning effectiveness in software engineering teamwork with over 70% accuracy [9]. Su et al. applied Random Forest, among other algorithms, to predict student submission timeliness, showcasing its versatility in different educational scenarios [10]. Random Forest proves to be a vital and comprehensive tool for predicting educational outcomes, adept at managing complex datasets and offering interpretable insights for advanced learning strategies.

C. Gaussian Naive Bayes

Gaussian Naive Bayes, a probabilistic classifier underpinned by Bayes' Theorem, is a pivotal tool in the predictive analytics arsenal, particularly in the educational sector [12]. This algorithm stands out for its application of Gaussian probability distribution to handle continuous data, a common characteristic in educational datasets.

The application of Gaussian Naive Bayes in predicting learning outcomes involves a nuanced approach. It models the likelihood of outcomes based on input features, which in this context are the learning outcomes of selected subjects. The algorithm assumes that the features follow a Gaussian (normal) distribution, an assumption that simplifies the computation of probabilities. The strength of Gaussian Naive Bayes in educational settings lies in its ability to handle large datasets efficiently and its robustness in dealing with uncertainty in data. Its simplicity and the probabilistic basis provide a clear understanding of how predictions are made, which is crucial in educational contexts where interpretability is as important as accuracy.

Several studies have demonstrated the effectiveness of Gaussian Naive Bayes in educational data analysis. Wijaya et al. [12] applied the Naive Bayes algorithm to predict student success rates in learning, achieving high accuracy. Ouissal Sadouni and Abdelhafid Zitouni [13] discusses the implementation of dynamic optimization of learning indicators using Naive Bayes Classifier, which is relevant to understanding the application of Gaussian Naive Bayes in educational settings. Gaussian Naive Bayes stands out for its simplicity, efficiency, and effectiveness in analyzing complex educational datasets, making it a crucial tool for educational data analytics.

D. K-Nearest Neighbors

The K-Nearest Neighbors (KNN) algorithm, a cornerstone in the realm of machine learning, is renowned for its simplicity and effectiveness in classification and regression tasks. This non-parametric method operates on the principle that similar instances are likely to be found in close proximity [14].

In the context of predicting learning outcomes, KNN's application involves using the learning outcomes of certain subjects as input to predict the outcomes of others. The algorithm identifies the 'k' nearest data points to a query point and predicts the outcome based on the majority vote of these neighbors. The choice of 'k' and the distance metric, typically Euclidean, are crucial in this process. KNN's applicability in predicting learning outcomes is attributed to its ability to adapt to the intrinsic structure of educational data, which often exhibits complex, non-linear relationships. Its model-free nature allows for a flexible approach to understanding and predicting educational outcomes [15].

Several studies have underscored the utility of KNN in educational settings. Hendrianto et al. utilized KNN, among other algorithms, to predict student performance in compulsory subjects, demonstrating its predictive power in academic environments [14]. Tribhuvan and Bhaskar explored machine learning techniques, including KNN, to enhance student learning experiences, further highlighting the algorithm's relevance in educational data analysis [15]. KNN excels in educational data analysis with its simple implementation and local data-based predictions, showing promise as a tool for learning outcome predictions despite challenges like data scale sensitivity.

E. Support Vector Regression

Support Vector Regression (SVR), an extension of the Support Vector Machine (SVM) algorithm, is a powerful tool in the domain of machine learning, particularly for regression tasks. SVR is designed to find a function that approximates the relationship between input and output variables in a high-dimensional space, making it suitable for complex prediction tasks [16].

In educational data analysis, SVR can be employed to predict learning outcomes. The algorithm takes as input the learning outcomes of selected subjects and predicts the outcomes of other subjects. The core of SVR lies in constructing a hyperplane in a multidimensional space that best fits the data points. The efficacy of SVR in predicting learning outcomes is attributed to its robustness against overfitting and its capacity to handle high-dimensional data.

Studies such as those by Pimentel et al. have demonstrated the application of SVR in educational settings, showcasing its potential in efficiently predicting student performance based on large datasets [16]. Another study by Huan Xu [17] introduces an innovative method for forecasting students' academic performance, which involves utilizing support vector regression (SVR) and enhancing it through the application of an improved dual algorithm.

III. Automation Process

The process of forecasting based on learner data is a multifaceted and intricate endeavor, requiring a harmonious integration of various stages including data collection, meticulous analysis, and the strategic application of advanced analytical techniques. In pursuit of optimizing this process, we propose a comprehensive and automated approach, encompassing a series of well-defined and interconnected steps. This automation process is not just a linear progression of tasks but a dynamic framework designed to adapt and evolve in response to the changing educational landscape and the diverse needs of learners. The automation process includes of following steps is illustrated in Fig. 1

1) Data collection: Learner data is amassed from various sources since their enrollment in university programs. This includes enrollment data like high school grades, English proficiency certificates, SAT scores, and aptitude assessments; and ongoing academic data such as grades, class attendance frequency, study hours, extracurricular activities, and more. This phase also involves identifying the most significant variables for forecasting purposes. The Student Information System (SIS) is a key data repository, storing demographic information (age, gender, nationality) and academic performance. However, socio-economic characteristics are not typically available in SIS, as they are often gathered through data collection methods like questionnaires. Additionally, learner information can be collected through Learning Management Systems (LMS) usage, including course data, grades, participation in discussions, and online exams and assignments.

2) Data preparation / preprocessing: Preparing data is crucial in data mining and involves making raw data suitable for mining techniques. Educational databases are often large, and the stored data frequently encounters quality issues. Hence, data cleansing methods are essential to handle missing, inconsistent, and outlier data to ensure data quality. Essential preprocessing methods include data cleaning, integration, reduction, and transformation.

- Data Cleaning involves removing noise and handling missing values to improve data quality.

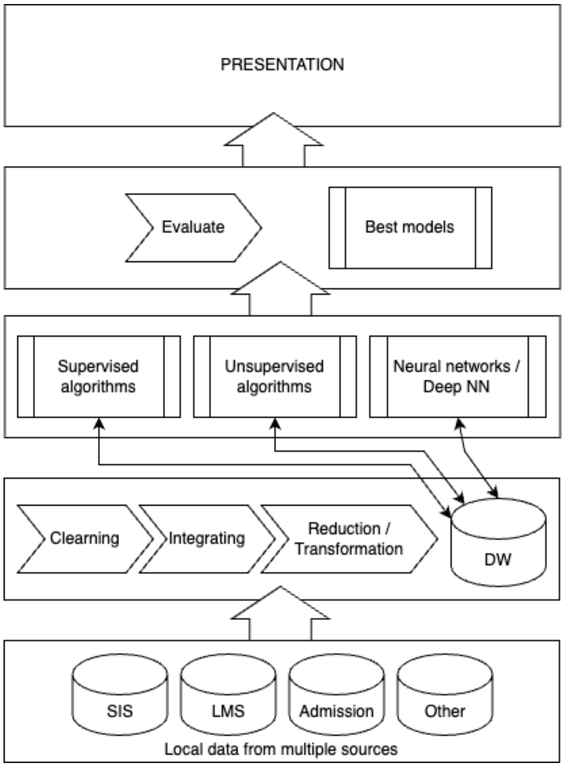


Fig. 1. Automation process.

- Data Integration combines data from multiple sources into a single source, addressing redundancy and inconsistency.
- Data Reduction transforms large datasets into smaller, information-rich datasets.
- Data Transformation modifies data into a form suitable for mining, including normalization and discretization.

Data after these steps are stored in a Data Warehouse (DW) which can be easily accessed for applying ML models in the next step.

3) Training ML models: This step involves using ML algorithms to analyze large data sets and identify patterns or trends. Both supervised and unsupervised learning models are employed to uncover interesting patterns in the data. Supervised learning uses labeled datasets to train models, which can then make predictions or classifications on new, unlabeled data. Unsupervised learning, on the other hand, involves analyzing data without any labels, aiming to identify patterns or clusters that can provide insights or aid decision-making. Classification and regression are two primary supervised learning techniques used for forecasting. Many more models/algorithms can be implemented and integrated into the system to provide flexibility in evaluating and selecting the best model for forecasting.

4) Model evaluation: Evaluating the performance of a classification model is a crucial step in developing and refining machine learning models. It allows for assessing the model's accuracy on test data. The original dataset is typically divided into two or three independent parts: a training set (validation/testing set) and a test set. The training set is used to build the model, the test set to evaluate its performance, and in the case of large data, a validation set to optimize hyper parameters. Common methods for dividing the dataset include holdout, random sampling, and cross-validation. The results of running models / algorithms in the previous steps are evaluated to select the best model for each specific task.

5) Presentation: The final step in the automation process involves meaningfully and understandably presenting the results and findings from the selected models. The presentation step aims to convey the insights gained from the data mining process to stakeholders like educators, administrators, policy-makers, and researchers in a format that supports decision-making and action.

IV. Experiment on Automation Process

We implement the automation process on a BI system described in our last paper [18]. The architecture of the BI system is shown in Fig. 2.

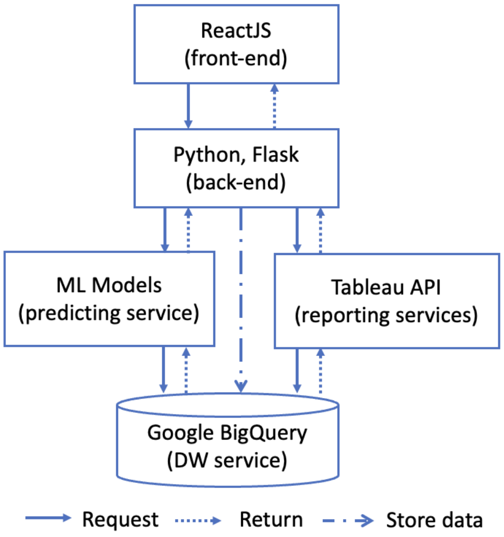


Fig. 2. The BI system.

In the back-end component, the steps of Data Collection and Data Preparation are executed seamlessly. This is followed by the Training ML models and the Model Evaluation steps, which are integral parts of the ML Models component. Subsequently, the Presentation step takes place in the front-end component. This component is a sophisticated web interface, designed to facilitate interaction with users through a web browser, ensuring a smooth and engaging user experience.

Using Data Collection and Data Preparation steps in the BI system, the authors have been updated the dataset to include data from years of 2022 and 2023, encompassing over 113,000 records. This dataset includes grades of students from three departments: Computing, Business Administration, and Graphic Design. In this experiment, the authors focused on the grades of Computing department.

A. Problem

Forecasting the academic performance in a subject based on the grades of previous subjects is a common and useful problem in the field of education. This not only helps students understand their abilities and developmental directions more clearly but also assists teachers and administrators in identifying and improving teaching methods as well as managing educational quality.

In the preceding discussion, this research will employ a dataset comprising grades from the Computing major to conduct experimental analyses. Specifically, a second-year course, designated as Advanced Programming (course code 1651), has been chosen as the focus for predicting academic outcomes namely, whether students pass or fail. This prediction will be based on the performance in a suite of first-year courses, which include Procedural Programming (1618), Programming (1619), Database Design & Development (1622), Website Design & Development (1633), Security (1623), and Managing a Successful Computing Project (1625). This approach allows for a detailed examination of the correlation between early academic performance and subsequent success in advanced coursework.

Following the data preparation phase, a selected subset of the requisite courses, encompassing the grades of 654 students, will be utilized for training and testing the predictive models. Within this subset, it is observed that approximately 80.6% of the students successfully passed the focal course 1651. Regarding the other courses integral to the prediction process, the average grades fluctuate, with the lowest mean grade being approximately 5.17 for course 1633 and the highest at around 5.93 for course 1619. Notably, course 1633 also exhibits the lowest pass rate at 68.81%, whereas course 1619 demonstrates the highest pass rate at 82.57%. These variations in pass rates and mean grades across different courses provide a comprehensive framework for analyzing and predicting academic performance in the Computing major.

B. Methods

To select the most effective model for prediction, the authors implemented the algorithms discussed in Section II and ran them on the same dataset to evaluate their outcomes. The model demonstrating the most optimal results was then chosen for integration into the automated forecasting process.

To assess the models' performance, the authors employed the k-folds verification technique with k = 10. Each model was trained and evaluated on each fold, calculating metrics such as Mean Squared Error (MSE), true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) and finally their average values on all the folds are returned. The correctness of the models was then determined based on the aggregation of true positives and true negatives across the data of each fold.

For all models, the authors trained and tested them on the same sub dataset of all grades from Computing Department. The sub dataset extracted from the main dataset had to ensure the inclusion of grades from all the relevant input and output courses, with at least one assessment per course. The total size of this qualified dataset comprised 654 students, making it suitable for running the predictive models.

All models uses the same inputs and output as described below:

- Input $X_1, X_2, X_3, X_4, X_5, X_6$: The average grades of assessments in first-year courses with codes 1618, 1619, 1622, 1633, 1623, and 1625.
- Output Y: Pass or fail outcome of a second-year course with the code 1651.

Next, we will see the result of training and testing on each model.

C. Experimental Result

1) Logistic regression result: To predict the binary outcome (pass/fail) of a second-year course (code 1651) using logistic regression we define the dependent variable, Y, represents the outcome of the course, coded as 1 for pass and 0 for fail. The independent variables, $X_1, X_2, X_3, X_4, X_5, X_6$, correspond to the average grades in six first-year courses with codes 1618, 1619, 1622, 1633, 1623, and 1625.

The logistic regression model is formulated as follows:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(w_0 + w_1 X_1 + w_2 X_2 + \ldots + w_6 X_6)}} \quad (1)$$

where, $w_0, w_1, \ldots, w_6$ are the model parameters that need to be learned.

The model is trained by minimizing the logistic loss function defined as:

$$J(w) = -\frac{1}{6} \sum_{i=1}^{6} \Big[y_{(i)} \log\big(\sigma(w \cdot X_{(i)} + b)\big) + (1 - y_{(i)}) \log\big(1 - \sigma(w \cdot X_{(i)} + b)\big) \Big] \quad (2)$$

where, σ denotes the logistic (sigmoid) function.

For prediction, the model estimates the probability of a student passing the 1651 course. A student is predicted to pass (Y=1) if $P(Y = 1|X) > 0.5$; otherwise, the student is predicted to fail (Y=0).

The performance of the Logistic Regression model was evaluated using the k-fold cross-validation technique with $k = 10$ as described above. The results of k-folds verification, all values are average values of k-fold, are shown in Table I.

TABLE I. Performance Metrics of the Logistic Regression Model

MSE	TN	FP	FN	TP	Correctness
0.17	4.2	3.0	2.0	20.8	83.33%

2) Random forest: To predict the binary outcome (pass/fail) of a second-year course (code 1651) using a Random Forest algorithm, the dependent variable, Y, is defined as the outcome of the course, coded as 1 for pass and 0 for fail. The independent variables, $X_1, X_2, X_3, X_4, X_5, X_6$, correspond to the average grades in six first-year courses with codes 1618, 1619, 1622, 1633, 1623, and 1625.

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification. The final prediction, $H(x)$, is the majority vote of the predictions made by individual trees, $h_1(x), h_2(x), \ldots, h_N(x)$, for N trees. In mathematical terms:

$$H(x) = mode\{h_1(x), h_2(x), \ldots, h_N(x)\} \quad (3)$$

Each tree is constructed using a random subset of the data, known as bootstrap sampling, and at each split in the tree, a random subset of the features is considered for splitting.

The Random Forest also uses out-of-bag (OOB) samples to estimate the error. The OOB error is the average error for each training sample, calculated using only the trees that did not have this sample in their bootstrap sample.

The effectiveness of the model was assessed through the application of the k-fold cross-validation method, wherein k was set to 10. The outcomes of this cross-validation, represented as mean values computed over all k-folds, are presented in Table II

TABLE II. Performance Metrics of the Random Forest Model

MSE	TN	FP	FN	TP	Correctness
0.11	5.4	1.8	1.4	21.4	89.33%

3) Support Vector Regression (SVR): SVR is a type of Support Vector Machine (SVM) that is used for regression challenges. While traditional SVM is used for classification tasks, SVR can be used to predict continuous outcomes. The main idea behind SVR in our problem is to find a function $f(x) = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4 + w_5X_5 + w_6X_6 + b$ that has at most ϵ deviation from the actual target values Y for all the training data, and at the same time is as flat as possible.

Mathematically, SVR solves the following optimization problem:

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \quad (4)$$

subject to

$$Y_i - (w_1 X_{1i} + w_2 X_{2i} + \ldots + w_6 X_{6i} + b) \leq \epsilon + \xi_i, \quad (5)$$

$$(w_1 X_{1i} + w_2 X_{2i} + \ldots + w_6 X_{6i} + b) - Y_i \leq \epsilon + \xi_i^*, \quad (6)$$

$$\xi_i, \xi_i^* \geq 0 \quad (7)$$

where, w is the weight vector, b is the bias, C is the regularization parameter, ξ and ξ^* are slack variables that allow for violations of the ϵ margin.

The efficacy of the SVR model was gauged utilizing the k-fold cross-validation approach, setting k at 10. The outcomes from the k-folds assessment, which are the mean values calculated across all k-folds, are outlined in the Table III.

TABLE III. Performance Metrics of the SVR Model

MSE	TN	FP	FN	TP	Correctness
0.133	4.6	2.6	1.4	21.4	86.67%

4) K-Nearest neighbors: The KNN algorithm operates by identifying the ‘K’ nearest neighbors of a given data point in the feature space. The Euclidean distance is commonly used as the distance metric, calculated as $d(X_i, X_j) = \sqrt{\sum_{n=1}^{N}(X_{in} - X_{jn})^2}$, where X_i and X_j are two points in an N-dimensional space.

In this application of the KNN algorithm, each student’s likelihood of passing or failing the second-year course (code 1651) is predicted based on the outcomes of the nearest neighbors in the dataset. These neighbors are identified by comparing the average grades in six other courses (codes 1618, 1619, 1622, 1633, 1623, and 1625) of each student. For a given student, the algorithm locates the ‘K’ students most similar in terms of their first-year grades and predicts the student as likely to pass (Y=1) or fail (Y=0) the 1651 course based on the most common outcome among these ‘K’ nearest neighbors. This can be represented as $Y = mode\{c_1, c_2, ..., c_K\}$, where c_i is the pass/fail outcome of each neighbor. Furthermore, a weighted voting approach can be employed where the influence of each of the ‘K’ neighbors on the prediction is inversely proportional to their grade distance from the student being classified, giving closer students (more similar in terms of grades) a higher influence in the prediction.

The KNN model’s effectiveness in forecasting the outcome of course 1651 was appraised through the k-fold cross-validation method, employing $k = 10$. Table IV shows the ensuing results represent the average values derived from the k-folds:

TABLE IV. Performance Metrics of the KNN Model

MSE	TN	FP	FN	TP	Correctness
0.18	3.0	4.2	1.2	21.6	82.00%

5) Gaussian Naive Bayes (GNB): In the context of the Gaussian Naive Bayes (GNB) model, we aim to predict the probability $P(Y = 1|X)$, which represents the probability of a student passing the course 1651 (coded as 1 for pass) given a set of relevant grades of other courses represented by the feature vector X.

- Y: A binary variable representing the result of 1651 course (pass or fail)
- X: A feature vector representing the grades $X_1, X_2, \ldots, X_6$, where X_i represents the grade in the respective course i.

The GNB model calculates the probability $P(Y = 1|X)$ using Bayes’ theorem, which relates the conditional probability $P(Y = 1|X)$ to the joint probability $P(X, Y)$ and the marginal probability $P(X)$:

$$P(Y = 1|X) = \frac{P(X|Y = 1) \cdot P(Y = 1)}{P(X)} \tag{8}$$

In this equation:

- $P(Y = 1|X)$: The probability of passing the course given the feature vector X
- $P(X|Y = 1)$ The probability distribution of the feature vector X when the student passes the course
- $P(Y = 1)$ The prior probability of passing the course
- $P(X)$ The marginal probability of observing the feature vector X

The GNB model assumes that each feature X_i follows a Gaussian distribution for each class (pass or fail). It calculates these probabilities based on training data and assumes that features are conditionally independent given the class label. In summary, the GNB model uses Bayes’ theorem and Gaussian distributions to estimate the probability of a student passing the course based on grades in other courses. It’s trained on labeled data to estimate Gaussian distribution parameters, including mean and variance, for each feature in both pass and fail classes.

The effectiveness of the GNB model in predicting the results of course 1651 was assessed using the k-fold cross-validation approach, with k set to 10. Presented in the Table V are the aggregated average results from these k-folds.

TABLE V. Performance Metrics of the GNB Model

MSE	TN	FP	FN	TP	Correctness
0.18	6.0	1.2	4.1	18.7	82.33%

D. Experiment Result Analysis

In this section, we present and analyze the results obtained from the k-fold cross-validation (with $k = 10$) for various predictive models: Logistic Regression, Random Forest, SVR, KNN, and GNB.

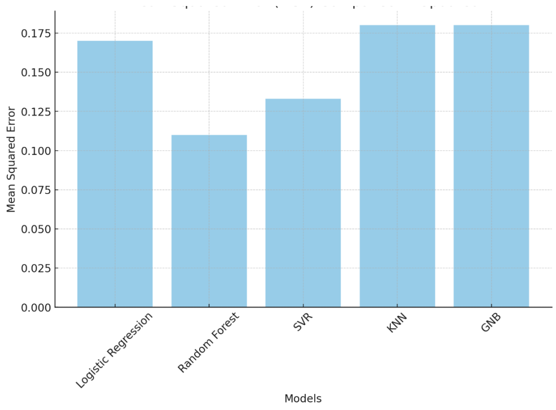


Fig. 3. Mean Squared Error (MSE) comparison.

1) Mean squared error comparison: As shown in Fig. 3, the Random Forest model demonstrated the lowest MSE (0.11), suggesting it as the most accurate among the evaluated models. Conversely, both KNN and GNB models exhibited the highest MSE (0.18), indicating relatively higher prediction errors.

2) Classification results: Classification results, including True Negatives (TN), False Positives (FP), False Negatives (FN), and True Positives (TP) counts, are essential for understanding a model’s capability in correctly classifying different

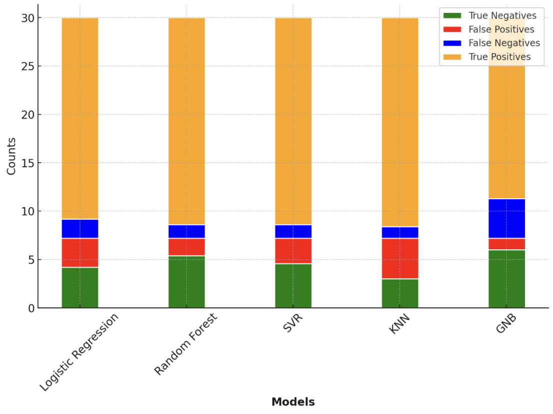


Fig. 4. Classification comparison.

outcomes. Fig. 4 illustrates a comparative analysis of these metrics. Notably, the Gaussian Naive Bayes (GNB) model excelled in identifying negative cases (TN), while the K-Nearest Neighbors (KNN) model slightly led in identifying positive cases (TP). However, the Random Forest model balanced false positives and false negatives effectively, indicating robust classification capabilities.

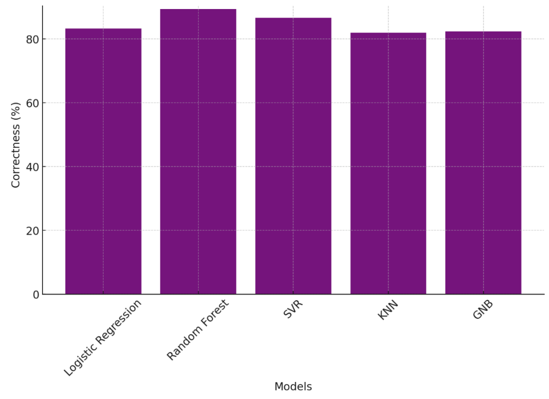
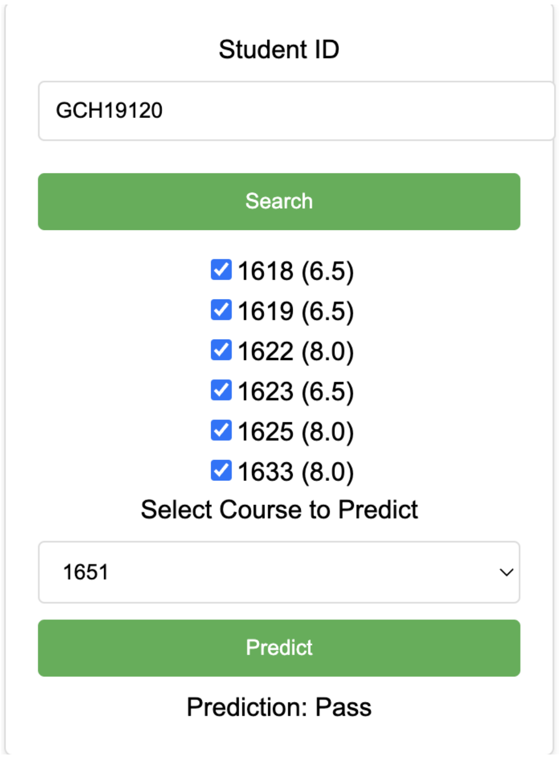


Fig. 5. Correctness comparison.

3) Correctness of models: The correctness percentage provides an overall effectiveness measure of the models. As depicted in Fig. 5, the Random Forest model outperformed others with the highest correctness percentage (89.33%). Despite high TP and TN rates in KNN and GNB models, respectively, their overall correctness percentages were lower, suggesting a trade-off between different types of classification errors.

4) Integration of predictive model: The analysis reveals that the Random Forest model exhibits a balanced and superior performance across various metrics, making it the most effective model among those tested. The GNB model, despite its high rate of TN, struggles in overall performance, indicating a potential issue in classifying positive cases. The KNN model, while showing a high TP rate, suffers from high MSE and lower correctness, pointing towards possible overfitting or poor generalization.

These insights suggest that further refinement and tuning of the Random Forest model could yield even better results.



Student ID

GCH19120

☑ 1618 (6.5)
☑ 1619 (6.5)
☑ 1622 (8.0)
☑ 1623 (6.5)
☑ 1625 (8.0)
☑ 1633 (8.0)

Select Course to Predict

1651

Prediction: Pass

Fig. 6. Predict 1651 course result.

Additionally, a deeper investigation into the feature selection and parameter optimization for the GNB and KNN models might improve their performance.

Based on the analysis, we integrate the Random Forest model into the Automation process. With a simple Web interface in the Presentation step, it allows user to predict the result of a course according to the grades of other selected courses as in Fig. 6.

We also did another experiment in which we select fewer courses. Since 1651 is a programming course (name: Advanced Programming), we select only programming related courses which are 1618 (Programming), 1622 (Database Design & Development) and 1633 (Website Design & Development). The result is shown in the Table VI.

TABLE VI. Performance Metrics of Various Models

Model	MSE	TN	FP	FN	TP	Correctness
RandomForest	0.133	5.1	2.1	1.9	20.9	86.67%
SVR	0.137	4.7	2.5	1.6	21.2	86.33%
KNN	0.163	4.1	3.1	1.8	21.0	83.67%
GaussianNB	0.163	6.0	1.2	3.7	19.1	83.67%
LogisticRegression	0.150	5.2	2.0	2.5	20.3	85.00%

The results indicate that the Random Forest model consistently achieves the lowest MSE and the highest level of accuracy. However, it's noteworthy that the accuracy of the Random Forest model shows a slight decline compared to its performance when trained with a more comprehensive dataset that includes both programming and theoretical courses. This observation raises an intriguing question: Does the inclusion of a broader selection of previous courses enhance the predictive accuracy of a model? Interestingly, this does not seem to be the case for other models like Logistic Regression or Gaussian Naive Bayes, suggesting that the relationship between the breadth of course selection and predictive accuracy is not straightforward and may vary across different ML models.

This further confirms the necessity of an automated process that involves implementing various ML algorithms to allow users to choose the best model after the evaluation step. Users can select different models/algorithms for different forecasting problems or even different models/algorithms for different subjects in a specific learning outcome forecasting problem.

V. Conclusion

Our study embarked on an journey to unravel the potential of integrating various machine learning models in an automation process to predict educational outcomes. The heart of our exploration was the rigorous experiment that tested models like Logistic Regression, Random Forest, KNN, and Gaussian Naive Bayes against the challenging task of forecasting course results.

The findings are illuminating. The Random Forest model, in particular, demonstrated exceptional proficiency, marked by the lowest MSE and highest correctness in predictions. This underscores its potential as a reliable tool in educational settings. Moreover, our analysis revealed an intriguing trend: the accuracy of predictions increases with the inclusion of more previous course grades. This insight is pivotal for educational institutions aiming to leverage data-driven approaches for student assessment and support.

Our study also emphasized the importance of a user-friendly interface in the Presentation stage, allowing educators and stakeholders to seamlessly interact with the predictive models. The practical application of our research, illustrated through a simple web interface, bridges the gap between complex algorithms and real-world usability.

In conclusion, this research marks a significant stride towards integrating machine learning in educational technology. It not only sheds light on the efficacy of various predictive models but also paves the way for future investigations. Areas ripe for exploration include enhancing model robustness and exploring their adaptability across diverse educational contexts. As we tread into this future, our endeavor remains rooted in the goal of harnessing technology to enrich learning experiences and outcomes.

Acknowledgment

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Enhancing K-means Clustering Results with Gradient Boosting: A Post-Processing Approach

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***Abstract*—As the volume and complexity of data continue to grow exponentially, finding efficient and accurate clustering algorithms has become crucial for many applications. K-means clustering is a widely used unsupervised machine learning technique for data analysis and pattern recognition. Despite its popularity, k-means suffers from certain limitations, such as sensitivity to initial conditions, difficulty in determining the optimal number of clusters, and the potential for misclassification. This research paper proposes an enhanced approach for improving the accuracy and performance of the k-means clustering algorithm by incorporating post-processing techniques using a gradient boosting algorithm. The proposed method comprises training the gradient boosting model on the labeled training set, i.e., the samples with correct cluster assignments obtained from the k-means algorithm, to predict the correct cluster assignments for the misclassified samples in the testing set. This results in refined cluster assignments for the testing set. The k-means algorithm is only used initially to cluster the data and obtain initial cluster assignments. The effectiveness of the proposed approach is validated through experiments on several benchmark datasets, and the results show a significant improvement in clustering accuracy and robustness compared to the standard k-means algorithm. The proposed approach has the potential to enhance the performance of k-means in various real-world applications and domains.**

Keywords*—K-means; gradient boosting; post-processing; misclassification; machine learning

I. Introduction

Enhancing the performance of clustering algorithms has become essential for obtaining accurate and effective clustering in the era of contemporary data, with its growing amount and diversity. Clustering is a strategy that is used for analyzing data, collecting similar data points together, and recognizing patterns in data that would otherwise be invisible [1]. There are several types of clustering algorithms, such as hierarchical methods, density-based methods, grid-based methods, and partitioning-based methods, each of which differs in the way they measure the similarity or distance between entities [2].

The k-means algorithm is an unsupervised algorithm that was improved by MacQueen in 1967 [3]. The k-means algorithm is a type of partitioning-based method that is used to group similar data. Each group of data is called a cluster. In the first stage, the algorithm randomly assigns an initial set of points for k clusters based on the nearest center of the clusters. Then, it modifies the points until it reaches the nearest cluster center. The process is iterative and continues until the centroids no longer update, resulting in the final centroids representing the ultimate centers of k clusters. The function of updating and modifying centroids is performed by calculating the distance measure specified in the algorithm [4].

The k-means algorithm offers several advantages, including its speed, simplicity, and ease of implementation [5]. It is useful in different applications such as marketing, recommendation systems, smart city services, the analysis of business data, and the analysis of user behaviors [6]. However, even with the advantages of the k-means algorithm, it still faces some drawbacks, such as its problem with local optima and its sensitivity to initial centroids. The k-means algorithm is sensitive to the centroids and will give different results whenever the initial centroids change [5]. In this study, we build upon a previous research paper that explored techniques for enhancing the k-means algorithm [7]. While acknowledging the contributions of the original work, we present an extended methodology that incorporates optimization techniques to further improve the clustering outcomes. The aim of this study is to surpass the performance achieved in the earlier study.

Several previous studies have been conducted in the field of improving the k-means algorithm. In [7], the authors presented a novel concept of post-processing the clusters obtained by the classical k-means algorithm to improve the quality of the resulting clusters. The post-processing approach consists of four steps that combine the k-means algorithm with a supervised learning algorithm, resulting in hybrid k-means-supervised learning (KM-SML). The paper proposed an approach to extract the majority of misclassified records from the clustered dataset and post-process them using the supervised machine learning algorithm. The results obtained from applying the proposed approach demonstrated significant improvements compared to the classical k-means algorithm. Precision and recall, two evaluation metrics, were used to assess the enhancements brought by the KM-SML approach. In both cases, better results were achieved using the KM-SML approach compared to the classical k-means algorithm. In [8], the researchers suggest a method that combines an optimization algorithm, namely Particle Swarm Optimization (PSO), with a k-means clustering algorithm. According to the comparison analysis, using PSO to determine the initial centroids yields promising results. While other studies highlight the benefits of combining metaheuristic optimization algorithms and data mining techniques, opening avenues for further research in this field, in [9], the researchers propose the integration of nature-inspired optimization algorithms, such as ant, bat, cuckoo, firefly, and wolf search algorithms with k-means clustering to overcome the drawback of getting stuck at local optima determined by random initial centroids. By combining these algorithms with k-means, the researchers aim to achieve unprecedented performance enhancements in terms of clustering accuracy. The results of the evaluation experiments show significant improvements in performance, particularly for the C-Bat and C-Cuckoo hybrid algorithms.

It is evident from the literature that researchers integrate various techniques with the k-means algorithm to achieve better outcomes or performance; Likewise, based on the previous work [7], this paper presents an enhanced approach for increasing the accuracy of the k-means algorithm by utilizing post-processing techniques with the gradient boosting algorithm. The proposed approach is implemented using the Python programming language and the Scikit-learn library [10] and applied to three datasets, which are the Iris dataset, Forest, and Banknote datasets [11], [12], and [13] respectively. The proposed approach implements the Split Criterion (SC) [7] for detecting potentially misclassified points. Additionally, the paper utilizes an extra set of threshold values for the SC and compares the results to other approaches [7], [14].

The proposed approach calculates the Euclidean distance of data points and the centroids of k clusters and scales the data using MinMaxScaler. Based on the SC threshold, the k-means results from the datasets are separated into training and testing sets. If the value of SC exceeds a predetermined threshold, the data point is considered a misclassified point and transferred to the test set, while the correct labels are transferred to the train set. The labels generated are used to train the gradient boosting classifier. As a result, the approach reached up to 97% accuracy on the Iris dataset. The approach presented in this paper assists in improving the performance of k-means clustering by minimizing the number of misclassified points, which helps to increase the accuracy of the algorithm.

The rest of the paper is organized as follows: Section II presents the literature review. Section III describes the techniques used in this paper. Section IV presents the results and discussion. Section V covers the conclusions.

II. Literature Review

The k-means method is an unsupervised clustering algorithm. It is extensively used in data mining because it is easy to use and understand and due to its applicability to various application domains [15]. The k in k-means represents the number of resulting clusters. The k-means algorithm accepts unlabeled data and groups it into k non-overlapping groups called clusters based on how close each point in a cluster is to the mean, called the centroid center, of that cluster [16].

In numerous papers, the k-means algorithm is combined with another algorithm to enhance execution efficiency, improve results, or achieve both. In [17], k-means and long short-term memory (LSTM) neural networks are used to analyze the behavior of electricity consumption for generating targeted marketing and recommending usage strategies. The data is first clustered using the k-means algorithm. Then, it is labeled based on a previous dataset and fed into LSTM to produce the results. The results are more accurate and efficient than using the LSTM directly. Instead of using LSTM, [18] uses a hybrid method that employs k-means with the Gaussian mixture model (GMM) for detecting malignant and benign breast cancer tumors using mammographic images. This approach has higher accuracy, signal-to-noise ratio, and a lower error rate than non-hybrid existing techniques such as k-means, GMM, and thresholding.

While [18] uses a hybrid model of k-means and GMM, [19] employs a hybrid model based on two evolutionary algorithms. It uses the fireworks-based and cuckoo-search-based evolutionary algorithms to improve the quality of the resulting clusters. In addition to these two algorithms, the method in [19] selects representatives of data using instance reduction to solve the empty cluster issue. The empty clusters problem happens when the number of clusters increases [20]. Moreover, this method enhances the selection of the initial centroids by using heuristics alongside evolutionary-based algorithms.

Both [21] and [22] use the Support Vector Machine (SVM) method with the k-means algorithm. Both techniques use k-means to cluster the values before inputting them into the SVM algorithm. In [21], the approach is to monitor and predict student performance in higher education. The resulting clusters from the k-means algorithm are further analyzed using SVM to accurately classify students as high-performing or low-performing students, which produces more accurate results than using the SVM only, whereas [22] uses the k-means algorithm on unlabeled data to generate a subset of the significant features to be the training set for the SVM instead of the complete dataset. According to [22], this approach improves the classification accuracy and performance in some situations compared to other approaches such as C-SVC and S4VM.

Unlike [21] and [22], which use SVM after k-means, [7] utilizes a supervised learning technique, in particular, the random forest classifier [23] is employed to improve the results of k-means. In addition, [7] proposes a method to detect potentially misclassified points. After applying the k-means algorithm to the Iris dataset [11], the results are examined for any potentially misclassified points. The detection of the misclassified points is done as follows, for each of the chosen minimum distances, divide each by the minimum distance to each cluster. If the values cross a predetermined threshold, then there is a possibility of misclassification for this point. After determining the possible misclassified points, they are extracted from the dataset, and the supervised learning algorithm is trained with the correctly clustered data. Finally, the misclassified points are entered into the model for classification. This proposed approach produces more accurate results than using the k-means method exclusively.

The k-means algorithm is sensitive to the initial clustering centers since the initial selection of centroids can affect the number of iterations and execution time [16]. To reduce the number of iterations and the running time, [6] have proposed reducing the dimensions of the data using percentile techniques and the Principal Component Analysis (PCA). The centroids are selected from the resulting reduced data. This technique has better results than both random and k-means++ initializations.

Another issue related to the selection of the cluster centers is that the non-optimal choice of centers leads the algorithm to converge to local minima [16]. Therefore, it is imperative to select the optimal centroid location to avoid getting stuck in local minima. The author in [14] proposes a method to determine optimal centers. This method employs an ant colony algorithm and uses positive and negative pheromone feedback to optimize the initialization of centroids. An additional issue is the instability of the assignment of clusters [16]. To overcome instability, [24] combines density and multiple clustering. This solution improves the running time and stability of the clustering by choosing the centroids according to the furthest distance and the highest density principle. However, solutions that use just density have a high time complexity [24].

Determining a suitable number of clusters requires domain knowledge [25]. Unfortunately, domain knowledge is not always readily available. To mitigate this issue, [26] proposes a method that does not require the manual specification of the number of clusters. One notable benefit of employing this method is its ability to accelerate the execution process and improves accuracy. It outperforms k-means when the data has lower dimensionality. Another proposed approach that does not require the specification of the number of clusters is in [27]. In [27], the authors propose and test a fully unsupervised k-means algorithm that does not need initialization and parameter selection. It auto-determines the optimal number of clusters using the entropy concept. In addition, it has good results when compared with the existing methods.

Traditional k-means implantations use the Euclidean distance to find the distances between the points [28]. However, [29] opted to use the evidence distance, which can deal with uncertainty. Instead of using the Euclidean distance, the method utilizes the evidence distance, resulting in higher accuracy and a reduced number of iterations. In contrast, [30] have proposed a k-means algorithm, L2-weighted k-means, whose mean is computed using the weighted feature space transformation. The L2-weighted k-means algorithm described in [30] was used to help in drilling for groundwater. Specifically, it was used to find the capacity of the average digging per day and to optimize profitability and productivity.

The authors of [31] state that the Lloyd algorithm for k-means does not perform well in dealing with large data. Therefore, [31] presents a k-means algorithm that uses neighbor information for assigning and updating the points. This algorithm reduces the distance calculations and increases the accuracy of the produced neighbors.

MapReduce, a programming model for parallel and distributed clusters, and Hadoop, a framework for distributed processing and storage of big data [32], have been used to enhance the scalability and parallelize the execution of k-means methods, as demonstrated in several studies [5], [19], [33]. The author in [5] describes a technique for news classification that uses MapReduce and Hadoop for parallelization. It also improves the selection of the initial centroids by leveraging the organizational structure of the data. The results show a 30% decrease in execution time over the method that does not employ parallelism.

Despite these efforts to enhance the performance of the k-means algorithm, gaps persist in the existing literature, including the reliance on domain knowledge for parameter selection or initialization, which limits applicability across diverse domains. Additionally, few methods provide a unified solution to address multiple shortcomings of k-means, such as sensitivity to initial conditions and misclassification issues. The proposed approach aims to bridge these gaps by introducing a post-processing technique using gradient boosting to refine cluster assignments obtained from k-means. Unlike prior methods that focus on specific enhancements or manual parameter tuning, the approach offers a comprehensive solution to improve clustering accuracy and robustness across various datasets and application domains.

III. Methodology

By adopting the data analysis techniques and the clustering approach, this research paper proposes an improvement to the performance of the k-means clustering algorithm by using gradient boosting in post-processing. The proposed approach intends to improve the quality of the k-means by post-processing the resulting clusters, which will contribute to delivering new insights in the context of clustering problems. This section describes the overall methodological approach of the present research paper by covering six fundamental elements. Section III-A describes the utilized datasets. The k-means clustering algorithm is then described in Section III-B. Section III-C provides an in-depth explanation of the split criterion technique. As well, Section III-D illustrates the post-processing methodology. Section III-E presents the evaluation matrices used to assess the proposed model. Eventually, the experimental setup is presented in Section III-F.

A. Datasets

The proposed approach is examined by using three benchmark datasets from the UCI Machine Learning Repository, which are popular datasets in the machine learning community. Namely, the Iris, Forest, and Banknote datasets [11], [12], and [13]. Table I describes the characteristics of each dataset, including the number of instances, the number of attributes, and the number of clusters for k-means. Additionally, a normalization technique is applied to the datasets in order to facilitate and improve the classification. The normalization is accomplished by using MinMaxScaler from the Scikit-learn toolkit [10] to scale each feature between 0 and 1. Consequently, the k-means outcomes utilizing the datasets are classified into training and testing sets based on SC results and the selected SC threshold. If the SC result of any point is higher than the predetermined SC threshold, the point will be added to the misclassified points, which are defined as the test sets to be used in the process of testing in the post-processing phase, while the correct labels are defined as the training set in the training process in the post-processing.

TABLE I. Datasets Description

Dataset	Instances	Attributes	Initial k
Iris [11]	150	4	k = 3
Forest [12]	523	27	k = 4
Banknote [13]	1372	5	k = 2

B. K-means Clustering Algorithm

The k-means algorithm is perhaps the most widely utilized clustering method. It has been explored for several decades. Therefore, it serves as the basis for several advanced clustering techniques [34]. The k-means algorithm is widely used because it uses straightforward, non-statistical principles, is extremely adaptable and flexible, and performs well. Furthermore, [34] mentions that the k-means algorithm is essentially composed of two phases. First, it assigns points to an initial set of k clusters. Second, it modifies and updates the assignment points. The process of assigning points is based on the nearest cluster center according to the distance function. Traditionally, k-means clustering uses Euclidean distance to compute the distance between points and the cluster centers [34]. Eq. (1) shows the distance metric formula used in this paper.

$$dist(x_i, y_c) = \sqrt{\sum_{j=1}^{a}(x_{ij} - y_{cj})^2}$$
$$i = 1, ..., n; \; c = 1, ..., k \tag{1}$$

where:

x is the data point

y is the centroid

n is the number of points

k is the number of clusters

a is the number of attributes

Consequently, updating and assigning points take place repeatedly until the cluster fitness is no longer improved by changes. The procedure ends at this stage, and the clusters are complete. Listing 1 shows the optimal values for the k-means parameters that produced the best outcomes.

Listing 1: k-means Parameters

```
KMeans(n_clusters=n, init='k-means++', n_init=10, max_iter
     =300, tol=0.0001,verbose=0, random_state=0, copy_x=True
     , algorithm='lloyd')
```

C. Split Criterion

In the proposed method, the SC [7] phase in the post-processing step plays a crucial role in determining potentially misclassified points by the k-means algorithm. This phase is significant for cluster analysis as it contributes to determining the accuracy of the clustering algorithm. It does this by finding and separating the likely misclassified points so they can be used as input for the final phase in post-processing.

Upon the completion of the k-means algorithm, k groups are generated, each of which comprises a center and a set of data points. In order to enhance the accuracy of clustering, misclassified data points must be identified and corrected. Here is where the SC method is applied.

The SC method begins by calculating the Euclidean distance between each data point and the centers of all clusters. For each point x, the minimum distance from it to each center is determined and referred to as min_{xc}. Then, min_{xc} is divided by the distance of each centroid to the point. This yields values between 0 and 1, representing the ratio of the minimum distance from point x to cluster c to each cluster center.

A threshold value between 0 and 1 is chosen to identify the misclassified data points. If any of the values calculated for data point x exceeds the chosen threshold, then x is considered misclassified. However, the point with the minimum distance to a cluster to which the point belongs is excluded from the comparison with the threshold since it will also result in 1.

For instance, if a point x_1 and three centers c_1, c_2, and c_3 are given, the distance between this point and the three cluster centers is calculated, resulting in three distances: $dist(x_1, c_1)$, $dist(x_1, c_2)$, and $dist(x_1, c_3)$. Then, the minimum distance, say $dist(x_1, c_2)$, is determined, and the SC result R of each distance can be calculated as follows:

$$SC(x_1, c_1) = \frac{dist(x_1, c_2)}{dist(x_1, c_1)} = R \quad 0 \leq R \leq 1 \tag{2}$$

$$SC(x_1, c_2) = \frac{dist(x_1, c_2)}{dist(x_1, c_2)} = R \qquad R = 1 \tag{3}$$

$$SC(x_1, c_3) = \frac{dist(x_1, c_2)}{dist(x_1, c_3)} = R \quad 0 \leq R \leq 1 \tag{4}$$

If the value obtained from Eq. (2) or (4) exceeds the specified threshold, the data point x_1 is considered misclassified. The minimum distance to the cluster, represented as $dist(x_1, c_2)$, is excluded from the comparison according to Eq. (3), resulting in a value of 1.

The SC method is a (moderate) technique for identifying misclassified data points in k-means clustering. By utilizing the threshold value, the SC technique can identify misclassified points so they can be minimized, thereby improving the accuracy of the clustering algorithm.

D. Post-processing Approach

Post-processing is a technique used with clustered data of k-means to improve the accuracy and quality of the resulting clusters [7]. In this phase, possibly misclassified labels are detected, and a corrective process is applied to obtain more accurate results. This study incorporates gradient boosting as a post-processing technique after applying the SC method. Gradient boosting is a popular machine learning method utilized for regression and classification tasks. It involves combining multiple weak models, usually decision trees, to form a powerful model that can make precise predictions. Gradient boosting is effective in handling imbalanced datasets, noisy data, and high-dimensional data [35].

To determine the optimal number of estimators for gradient boosting, a method is employed where the data is divided into training and testing sets, and multiple iterations of training and testing are conducted. Various ranges of estimators are tested, and the results are compared to identify the ideal number. The experiments indicate that the best outcomes were obtained with 100-200 estimators.

Gradient boosting also requires additional parameters such as learning rate, maximum depth, and random state. The best values for these parameters are found using a grid search technique, which entails trying a range of values for each parameter and choosing the combination that results in the highest performance [36]. However, in this study, the default values provided by the library were used for these parameters, as they are generally well-suited for a wide range of scenarios and models, as shown in Listing 2.

Listing 2: Gradient Boosting Parameters

```
ensemble.GradientBoostingClassifier(loss='log_loss',
     learning_rate=0.1, n_estimators=100, subsample=1.0,
     criterion='friedman_mse', min_samples_split=2,
     min_samples_leaf=1, min_weight_fraction_leaf=0.0,
     max_depth=3, min_impurity_decrease=0.0, init=None,
     random_state=None, max_features=None, verbose=0,
     max_leaf_nodes=None, warm_start=False,
     validation_fraction=0.1, n_iter_no_change=None, tol
     =0.0001, ccp_alpha=0.0)
```

The k-means clustering algorithm's performance was successfully enhanced by employing gradient boosting during the phase of post-processing. The proposed approach substantially increased algorithm accuracy through the detection of potentially misclassified labels and the attempts to correct them. Algorithm 1 demonstrates the process of training, testing, and evaluating the performance of the gradient boosting algorithm in the post-processing phase.

Algorithm 1 Gradient Boosting in the Post-processing Phase

```
Input: Correctly labeled set $X_{train}, y_{train}$ and the misclassified set $X_{test}$
Output: Predicted labels $y_{pred}$ for all dataset
Set the parameters for the gradient boosting algorithm
Train the gradient boosting classifier on $X_{train}$ and $y_{train}$
$y_{test} \leftarrow$ Apply the trained gradient boosting classifier on $X_{test}$
$y_{pred} \leftarrow \textsc{Append}(y_{train}, y_{test})$
Evaluate classifier performance using evaluation metrics (accuracy, precision, recall, F1-score) on the corrected labels.
return $y_{pred}$
```

E. Evaluation Metrics

The performance of the proposed approach is evaluated in terms of classification accuracy, precision, recall, and F1 scores to the formerly indicated datasets. The evaluation metrics are calculated using the following equations, which are measured by utilizing the true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Accuracy represents the number of correctly classified data instances over the total number of data instances. Eq. (5) shows the accuracy formula:

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN} \tag{5}$$

The precision result represents the positive predictive value in the classified data instances. Eq. (6) shows the precision formula:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

The recall value represents the true positive rate of data instances. Eq. (7) shows the recall formula:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

The F1 score represents the harmonic mean of both precision and recall. Eq. (8) shows the F1 score formula:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

The results of all the evaluation metrics used to measure the performance of the proposed approach on the previously described datasets are discussed in the Results and Discussion section.

F. Experimental Setup

For the experimental setup, the proposed method is implemented using the Python programming language. The libraries NumPy, Pandas, and Scikit-learn are chosen for their ease of use and their popularity in the machine learning community. The experiments are conducted on a computer with an Intel Core i7 processor and 16GB of RAM.

As mentioned previously, Iris, Forest, and Banknote are the three UCI datasets that were employed in the experiment. After obtaining clustered data with k-means, each data is split using SC into correctly classified points, a training set, and possibly misclassified points, a testing set. Then, the training set employed to train the model using the training set processed by the k-means algorithm. These labeled data are stable and will not be modified after the post-processing phase is performed. Furthermore, the testing set containing all misclassified labels is fed forward to the trained model, which modifies the labels to obtain correct and enhanced results.

The proposed approach is conducted using the following steps:

Step 1. Normalize the dataset using the MinMaxScaler.

Step 2. Process the normalized data by the k-means algorithm to produce a k number of clusters.

Step 3. Split the clustered data using the SC method. The correct labels are used as the training set for the gradient boosting algorithm, while the misclassified labels are stored for later use.

Step 4. Predict the labels for the misclassified data. The final result is obtained by combining the correct and predicted labels.

The entire process of the proposed method is shown in Fig. 1.

Eventually, the results of the experiments have demonstrated that the post-processing accompanied by SC and gradient boosting approaches is a powerful tool for enhancing the results of the k-means clustering algorithm. The approach offers a flexible and effective method to refine the results of the k-means algorithm, making it a valuable tool for various applications and datasets. A comprehensive and detailed presentation of the results is provided in the Results and Discussion section of the research.

IV. Results and Discussion

The outcomes of the experiment that has been successfully and effectively conducted, based on the mentioned steps earlier, will be detailed and compared to other approaches from [7], [14] in this section. The section is divided into three subsections. The first subsection is to show the SC results and understand the effect of various threshold values. In the second subsection, the enhanced accuracy of the supervised model employing the gradient boosting algorithm is presented

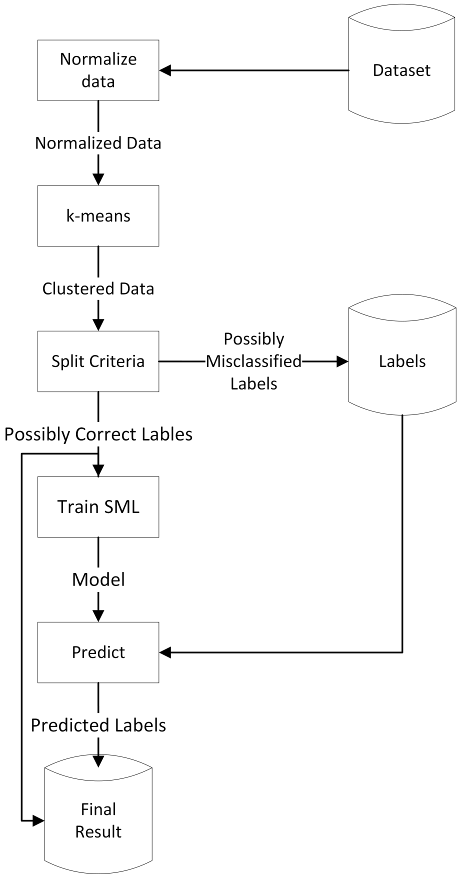


Fig. 1. A flowchart of the proposed approach.

and compared against random forest for the Iris dataset. For the last subsection, the enhanced model is compared with other improved k-means algorithms, and the model outperforms all of them in two datasets. Before showing the post-process results, the accuracy of k-means for the three datasets needs to be shown. It is as follows:

- 89% for the Iris dataset (133 out of 150 correctly clustered).
- 55% for the Banknote dataset (790 out of 1372 correctly clustered).
- 77% for the Forest dataset (405 out of 532 correctly clustered).

A. Split Criteria

The split criteria are used to detect misclassified points, but its modest and adequate mechanism could also identify correctly classified points as misclassified. Choosing a specific threshold for split criteria is not straightforward. Therefore, a range of values for the threshold is sufficient to work on all datasets. The study of split criteria has been accomplished previously for the Iris dataset using three variables: total points, correctly classified points, and misclassified points [7]. In this study, a new variable called "remaining misclassified points" is introduced, which represents the points that should have been detected as misclassified by the split criteria. Additionally, the exploration of various threshold values for the split criteria is conducted. Furthermore, the study is extended with two additional datasets, the Banknote and Forest datasets.

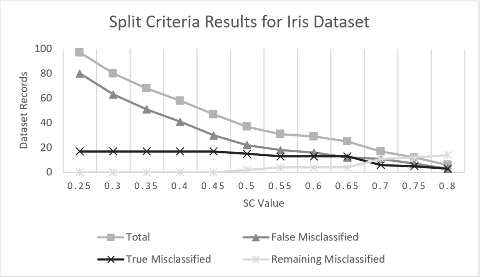


Fig. 2. Split criteria results for iris dataset.

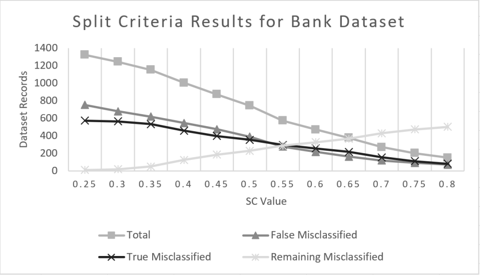


Fig. 3. Split criteria results for banknote dataset.

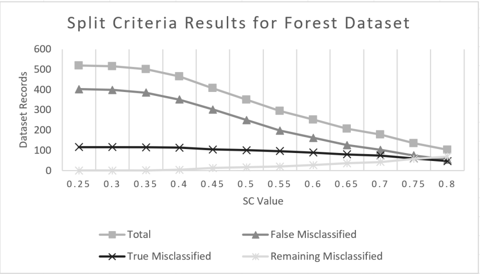
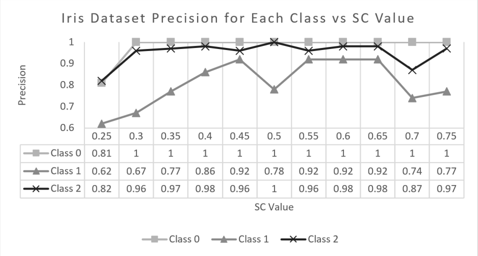


Fig. 4. Split criteria results for forest dataset.

Based on a previous study of the SC results for the Iris dataset, the appropriate threshold values for balanced results are between 0.4 and 0.6 [7]. With the previous conclusion as a guide, this study confirms that threshold values between 0.4 to 0.6 are also sufficient for all three datasets. When the threshold value is small, all misclassified points are almost detected right, true misclassified, as shown in Fig. 2, 3, and 4 precisely at 0.25 SC value. At the same time, the points that are correctly clustered by k-means are also considered as possibly misclassified points, false misclassified. Accordingly, gradually increasing the threshold value decreases both true and false misclassified while increasing the remaining misclassified points that should be detected as misclassified. Unfortunately, a compromise should be made by choosing balanced results for the threshold value with the main focus on decreasing the remaining misclassified points as much as possible, as follows: 0.45-0.65 for the Iris dataset as shown in Fig. 2, 0.35-0.50 for the Banknote dataset as shown in Fig. 3, 0.4-0.6 for Forest dataset as shown in Fig. 4. Therefore, continuing to use the same range for the threshold between 0.40 and 0.60 seems reasonable while also considering comparing results and being consistent with previous findings. In addition, the SC threshold value is incremented by 0.5. Therefore, the set of points within the two endpoints [0.40,0.60] are 0.40, 0.45, 0.50, 0.55, and 0.60.

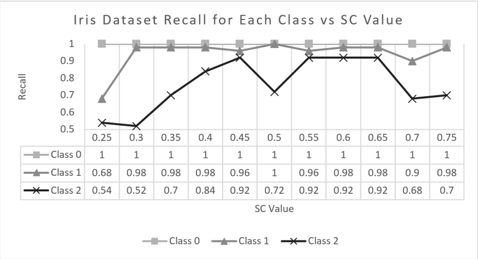
B. Gradient Boosting Post-process for the Iris Dataset

The Iris dataset has 150 data points and three classes, each with 50 data points [11]. This section focuses on presenting the results obtained from processing the Iris dataset exclusively. The results of post-process precision and recall for each class of the Iris dataset with a set of threshold points between two endpoints [0.25, 0.75] are shown in Fig. 5 and 6. The two figures represent the three classes as Class 0, Class 1, and Class 2. In addition, each figure is associated with a data table containing the precise percentage value. The data table is essential in this context as the Iris dataset has been used extensively in testing algorithms, and even a slight variation in the percentage is considered a significant accomplishment. A comparison of precision and recall results with random forest results is shown in Table II. This paper uses k-means with gradient boosting, abbreviated as K+GB, while the previous work has used k-means with random forest, abbreviated as K+RF. Besides precision and recall, the accuracy of both models is set out in Table III. Both Tables II and III illustrate the results of a set of threshold values between 0.40 and 0.60. It is apparent from both tables that a few cell values are empty. All these missing values are related to random forest results since the previous experiment did not provide the results of either 0.45 or 0.55 threshold values.



	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75
Class 0	0.81	1	1	1	1	1	1	1	1	1	1
Class 1	0.62	0.67	0.77	0.86	0.92	0.78	0.92	0.92	0.92	0.74	0.77
Class 2	0.82	0.96	0.97	0.98	0.96	1	0.96	0.98	0.98	0.87	0.97

Fig. 5. Iris dataset precision for each class vs. SC Value.



	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75
Class 0	1	1	1	1	1	1	1	1	1	1	1
Class 1	0.68	0.98	0.98	0.98	0.96	1	0.96	0.98	0.98	0.9	0.98
Class 2	0.54	0.52	0.7	0.84	0.92	0.72	0.92	0.92	0.92	0.68	0.7

Fig. 6. Iris dataset recall for each class vs. SC Value.

Class 1 and 2 misclassified points are misallocated between Class 1 and 2, while all Class 0 points hold steady along all threshold values except at 0.25, as seen in Fig. 5 and 6. What stands out in both figures is the 100% precision and recall for Class 0, except at 0.25, which has 81% precision but still has 100% recall. Obviously, misclassified points are only within Class 1 and Class 2. Class 2 has higher precision than Class 1, while Class 1 has higher recall than Class 2. Further statistics by calculating the average reveals that the model precision percentage is less than 90% at three threshold values: 0.25, 0.30, and 0.70 with 75%, 88%, and 87% precision, respectively. In contrast, the recall percentage is less than 90% at five different threshold values: 0.25, 0.30, 0.35, 0.70, and 0.75 with 74%, 83%, 89%, 86%, and 89% recall, respectively. Overall, excellent results are easily observed at four different threshold values.

Without including rows with missing values, the proposed model outperforms random forest by two out of three threshold values in Class 1 and Class 2 in Table II and accuracy in Table III. In Table II, for Class 1, the model's precision is better at 0.40 and 0.60, and its recall is better at 0.40 and 0.50. Accordingly, for Class 2, the model's precision is better at 0.40 and 0.50, and its recall is better at 0.40 and 0.60. Moreover, in Table III, its accuracy is higher for both 0.40 and 0.60. The most interesting point of these results is that the random forest's best result is at a 0.60 threshold value with 94% accuracy. In contrast, the best accuracy for the proposed model is at the same threshold value with 97% accuracy.

C. Gradient Boosting Post-process vs. Other Improved K-Means

The proposed model has been tested with two additional datasets besides the Iris dataset, and the findings are presented with the results of other approaches as benchmarks. The model's accuracy and average accuracy using a set of threshold values are reported in Table V. The average accuracy is calculated for two reasons. First, the approach implemented can not be validated by one threshold value to be viable for comparison with other approaches. Second, the other approaches used as benchmarks have presented their accuracy values by taking the average values after running the algorithms several times. Therefore, Table IV compares the obtained average accuracy from the proposed model with four other algorithms: k-means, FCM, three-way k-means, and improved three-way k-means [14]. The accuracy is the only finding reported in this section.

The proposed method using gradient boosting outperforms other algorithms with two out of three datasets for one algorithm and three out of three for the rest of the algorithms as reported in Table IV. After obtaining the accuracy for the set of points between 0.40 and 0.60 threshold values as shown in Table V, the average accuracy is calculated as 94.67% for the Iris, 63.24% for the Banknote, and 78.61% for the Forest datasets. The proposed approach outperforms all algorithms for the Iris and Banknote datasets, achieving an approximate increase in accuracy of 4% and 2%, respectively. Only for the Forest dataset, the model slightly exceeds all algorithms except for the improved three-way k-means.

V. Conclusion

Clustering algorithms are frequently used to identify dispersed patterns and group them into clusters. In order to improve the quality of the k-means clustering algorithm, this research paper has been introduced. The proposed research paper enhances the performance of the k-means clustering

TABLE II. IRIS DATASET PRECISION AND RECALL FOR K-MEANS + RANDOM FOREST (K+RF) VS. K-MEANS + GRADIENT BOOSTING (K+GB)

EM	Precision						Recall					
Classes	Class 0		Class 1		Class 2		Class 0		Class 1		Class 2	
SC	K+RF	K+GB	K+RF	K+GB	K+RF	K+GB	K+RF	K+GB	K+RF	K+GB	K+RF	K+GB
0.40	1.00	1.00	0.84	0.86	0.95	0.98	1.00	1.00	0.96	0.98	0.82	0.84
0.45	-	1.00	-	0.92	-	0.96	-	1.00	-	0.96	-	0.92
0.50	1.00	1.00	0.86	0.78	0.98	1.00	1.00	1.00	0.98	1.00	0.84	0.72
0.55	-	1.00	-	0.92	-	0.96	-	1.00	-	0.96	-	0.92
0.60	1.00	1.00	0.85	0.92	1.00	0.98	1.00	1.00	1.00	0.98	0.82	0.92

TABLE III. ACCURACY OF POST-PROCESSES: RANDOM FOREST VS. GRADIENT BOOSTING

SC	K+RF	K+GB
0.40	0.93	0.94
0.45	-	0.96
0.50	0.94	0.91
0.55	-	0.96
0.60	0.94	0.97

TABLE IV. AVERAGE ACCURACY COMPARISON BETWEEN K-MEANS + GRADIENT BOOSTING AND OTHERS

Datasets	K-Means	FCM	Three-Way k-Means	Improved Three-Way k-Means	K-Means+GBA
Iris	0.8866	0.8933	0.9040	0.9040	0.9467
Banknote	0.5758	0.5969	0.6123	0.6131	0.6324
Forest	0.7795	0.7540	0.7807	0.8294	0.7861

TABLE V. ACCURACY OF K-MEANS + GRADIENT BOOSTING FOR THE THREE DATASETS

SC	Iris	Banknote	Forest
0.40	0.9400	0.6407	0.7462
0.45	0.9600	0.6465	0.8026
0.50	0.9067	0.6458	0.7838
0.55	0.9600	0.6443	0.7932
0.60	0.9667	0.5845	0.8045
Average	0.9467	0.6324	0.7861

algorithm by employing gradient boosting as a post-processing phase. Consequently, the proposed model optimizes misclassified candidate clusters from the k-means algorithm by post-processing them using the gradient boosting algorithm. Across three well-known benchmark datasets, the proposed approach performance is assessed in terms of accuracy, precision, recall, and F1 score. According to the experimental outcomes, the proposed model achieved an average accuracy of 94.67% for the Iris dataset, 63.24% for the Banknote dataset, and 78.61% for the Forest dataset. The outcomes of the proposed model confirm its effectiveness and demonstrate its applicability to a wide variety of clustering problems. Thus, several real-life domains can take advantage of the proposed model in order to enhance the data analysis process. The proposed approach has been explored on a limited number of benchmark datasets that do not encompass real-world data. For this reason, the model's capacity for generalization is likely to be optimized in future research. Eventually, based on these principles, future research will concentrate on enhancing the accuracy of the proposed model by utilizing a real-world dataset, assimilating it with other learning approaches, and offering a sophisticated split criteria technique to achieve more promising outcomes.

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Optimizing Grape Leaf Disease Identification Through Transfer Learning and Hyperparameter Tuning

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***Abstract*—Grapes are a globally cultivated fruit with significant economic and nutritional value, but they are susceptible to diseases that can harm crop quality and yield. Identifying grape leaf diseases accurately and promptly is vital for effective disease management and sustainable viticulture. To address this challenge, we employ a transfer learning approach, utilizing well-established pre-trained models such as ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3, renowned for their exceptional performance across various tasks. Our primary objective is to identify the most suitable network architecture for the classification of grape leaf diseases. This is achieved through a rigorous evaluation process that considers key metrics such as accuracy, F1 score, precision, recall, and loss. By systematically assessing these models, we aim to select the one that demonstrates the best performance on our dataset. Following model selection, we proceed to the crucial phase of fine-tuning the model's hyperparameters. This fine-tuning process is essential to enhance the model's predictive capabilities and overall effectiveness in disease identification. To accomplish this, we conduct an extensive hyperparameter search using the Hyperband strategy. Hyperparameters play a pivotal role in shaping the behavior and performance of deep learning models, and by systematically exploring a wide range of hyperparameter combinations, our goal is to identify the most optimal configuration that maximizes the model's performance on the given dataset. Additionally, the study's results were compared with those of numerous relevant studies.**

Keywords*—*Grape disease recognition; disease identification; transfer learning; hyperparameter optimization; hyperband strategy; fine-tuning; deep learning

I. Introduction

The presence of plant diseases can result in a notable reduction in agricultural yields, causing decreased crop productivity and financial setbacks for farmers [1], [2], [3], [4], [5], [6]. Prompt identification and timely management of these diseases are essential to minimize their adverse consequences and optimize crop yields. Swift detection and intervention strategies are key to preventing disease outbreaks and fostering sustainable crop production. Through swift detection and proactive measures against plant diseases, farmers can employ suitable control methods like precise fungicide applications or crop rotations to reduce yield losses and protect their harvests [7], [8]. Furthermore, timely disease detection can also assist in preventing the spread of diseases to nearby plants, preserving the overall well-being of agricultural ecosystems. Traditional approaches for diagnosing plant diseases have been acknowledged as problematic and ineffective in numerous agricultural contexts. These methods often depend on visual symptoms and physical inspections, posing challenges in accurately identifying diseases, particularly during their initial development stages. Relying solely on visual symptoms can be deceptive, as various diseases may manifest similar signs, resulting in misdiagnoses and improper treatments. Additionally, these traditional methods may not effectively detect pathogens that lack visible indications on plant surfaces, adding complexity to the diagnostic procedure. Acknowledging these constraints, there has been an increasing focus on embracing contemporary technology-driven solutions, including advanced image-based recognition systems and artificial intelligence-based methods, to enhance the precision and efficiency of plant disease diagnosis and management. Deep Learning (DL) and Machine Learning (ML) techniques have gained extensive utilization in image recognition applications across diverse fields. Including medicine [9], [10], [11], [12]. In self-driving cars [13], [14], [15], [16], [17], [18]. In agriculture [19], [20], [21], [22], [23]. Especially when it comes to automating the identification of plant diseases [24], [25], [26], [27], [28], [29], [30], etc.

This article makes a significant contribution to the agricultural and viticulture sectors by addressing the substantial challenges associated with grape disease management and precise identification. The study's primary contribution lies in the adoption of advanced technological solutions, including transfer learning and pre-trained models renowned for their exceptional performance such as ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3. By employing these cutting-edge techniques, the research aims to provide more accurate and efficient grape leaf disease classification, thereby bolstering disease management strategies. Additionally, the study highlights the critical role of fine-tuning model hyperparameters through extensive hyperparameter searches, which is pivotal in enhancing the predictive capabilities and overall effectiveness of the selected model. This comprehensive approach serves to optimize grape disease management and advance sustainable viticulture practices, making a valuable contribution to the field of agricultural research and disease management.

The structure of the paper is as follows: A comprehensive review of the literature is provided in Section II. The Grape Disease Recognition Methodology, comprising the Data Set, Data Preparation, and Model Evaluation Metrics, is described in Section III. Section IV describes the experimental system and final results. Section V provides a summary of the study's results, concluding notes, and a comparison of current approaches to our suggested model for a similar problem. Lastly, Section VI outlines potential avenues for future study.

II. Related Works

Recent advancements in deep learning methodologies, in particular, convolutional neural networks (CNNs) and models of transfer learning (TL), have demonstrated significant progress in automating agricultural disease identification techniques. Multiple studies have explored the utilization of deep learning techniques to identify leaf diseases in general, including grape leaves in particular. Researchers are actively exploring innovative approaches to enhance the accuracy of disease identification.

Ullah, Zahid, et al. in [31] introduces a hybrid deep learning (DL)-based approach, combining EfficientNetB3 and MobileNet into the EffiMob-Net model, to accurately detect tomato plant diseases from leaf images. The study addresses overfitting by employing techniques like regularization, dropout, and batch normalization. The proposed EffiMob-Net model achieved a 99.92% success rate in accurately identifying tomato leaf diseases when evaluated on a dataset of diseased and healthy tomato leaf images, highlighting its excellent feature extraction capabilities.

In [32], Jing, Jiaping, et al. visually differentiates between nine different infectious diseases in tomato leaves and healthy leaves. The study applied EfficientNetB5 to a dataset of tomato leaf diseases (TLD) without segmentation, achieving an impressive average test accuracy of 99.07%. To enhance model interpretability, the paper introduces the use of gradient-weighted class activation mapping (GradCAM) and local interpretable model-agnostic explanations. This interpretability is vital for improving predictive performance, fostering trust, and enabling the integration of the model into agricultural practices.

In [33], the authors have developed a lightweight model for identifying tomato leaf diseases, which they named LightMixer. This model combines a depth convolution with a Phish module and a light residual module. Experimental findings reveal that the LightMixer model achieved an impressive 99.3% accuracy when tested on public datasets, all while maintaining a minimal parameter count of 1.5 million.

In [34], the authors introduce a pipeline for automated tomato leaf disease identification, incorporating three compact convolutional neural networks (CNNs). They leverage transfer learning to extract deep features from The final fully connected layer within the Convolutional Neural Networks (CNNs), resulting in a more concise and high-level representation. These features are then combined from all three CNNs to harness the strengths of each structure, followed by the application of a hybrid feature selection method to generate a comprehensive feature set with reduced dimensions. Notably, the results demonstrate that the K-nearest neighbor and support vector machine classifiers achieved remarkable accuracy, reaching 99.92% and 99.90%, respectively, using a minimal feature set of 22 and 24 features.

The authors in [35] introduces a convolutional neural network-based model for the identification and classification of tomato leaf diseases. The model is trained using a publicly available dataset and supplemented with field photographs. To prevent overfitting, generative adversarial networks are employed to generate data with similar characteristics to the training set. The results demonstrate the model's exceptional performance, with an accuracy exceeding 99% on both the training and test datasets in the detection and classification of tomato leaf diseases.

In [36], an integrated deep learning solution is introduced for the detection and classification of banana diseases. The approach involves the examination of various parts of the banana plant, not just the leaves, utilizing convolutional neural networks (CNN) and a combined binary and multiclass Support Vector Machine (FSVM). This method yields outstanding results, with an impressive overall accuracy of 99%, alongside excellent precision-recall and F1-score performance metrics.

The research in [37], an efficient method for detecting rice plant diseases is developed, leveraging convolutional neural networks. The study concentrates discusses three major rice illnesses: leaf smut, brown spot (caused by fungus), and bacterial leaf blight (caused by bacteria). The proposed approach focuses on recognizing and identifying these diseases based on the size, shape, and color of lesions in rice leaf images. By employing Otsu's global thresholding method for binarizing images, background noise is effectively removed. The fully connected CNN model, trained with 4000 samples of each diseased and healthy rice leaf, demonstrates impressive performance, reaching 99.7% accuracy on the dataset.

The research in [38] introduces a CNN model for the classification of rice and potato plant leaf diseases. The study employs a dataset of 5932 rice leaf images and 1500 potato leaf images. The proposed CNN model effectively captures hidden patterns in raw images, achieving an impressive accuracy of 99.58% for rice leaf classification and 97.66% for potato leaves. The results reveal that the CNN model outperforms other machine learning image classifiers, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest.

The authors in [39] presents a novel approach for precise detection and classification of rice leaf diseases, utilizing a Deep Convolutional Neural Network (DCNN) with transfer learning. The method includes a modification of the VGG19-based transfer learning technique and successfully detects and diagnoses six distinct classes of rice leaf diseases. The maximum average accuracy achieved is 96.08% when using a non-normalized augmented dataset, with corresponding values of 0.9620 for precision, 0.9617 for recall, 0.9921 for specificity, and 0.9616 for the F1-score.

In [40], the authors employ convolutional neural network (CNN) methods to address the classification of five distinct potato disease classes, including Healthy, Black Scurf, Common Scab, Black Leg, and Pink Rot. Their study utilizes a dataset of 5000 potato pictures and compares their classification results with various alternative techniques, including Transfer Learning, R-CNN, VGG, Alexnet, and Googlenet. Notably, the deep learning method proposed in the paper outperforms existing approaches, achieving accuracy rates of 100% and 99% in some of the individual disease classes.

In [41], the impact of hyperparameters and training approaches on model performance is examined. The study evaluates the performance of four deep learning models, with three trained from scratch and one using a pre-trained ResNet50 model, in the context of detecting potato plant diseases, specifically early blight and late blight, using the plant village dataset. The experimental results demonstrate that models trained from scratch outperform the pre-trained ResNet50 model, achieving accuracies of 96.75% and 94.43% compared to 93.5%. This suggests that pre-trained models may not always be the best choice for all datasets.

The study in [42] introduces an efficient deep learning-based solution to detect crop diseases, effectively preventing disease spread and ensuring healthy plant growth. In the experiment, the model achieved an impressive overall accuracy of 99.55% in identifying three diseases in corn, potato, and tomato. Furthermore, individual testing of these plants revealed classification accuracies of 98.44% for corn, 99.43% for potato, and 95.20% for tomato, showcasing the effectiveness of the proposed model.

The author in [43] conducts a comprehensive exploration of deep transfer learning and deep convolutional neural networks (CNNs). The primary focus of the research is to put carried out a model that has been pre-trained, specifically ResNet50 for plant disease detection and classification, utilizing the ImageNet dataset. Corn (maize) and Potato images from the plant village dataset are used to assess the model's performance. The model processes input images of Corn (maize) or Potato leaves through preprocessing techniques like data augmentation and segmentation before using the Resnet50 model. The evaluation of the Resnet50 model yielded the following results: 98.0% accuracy, 77.0% precision, 99.0% recall, and 86.0% F1-score.

The study in [44] explores the use of well-known Convolutional Neural Network (CNN) models—EfficientNetB5, MobileNet, ResNet50, InceptionV3, and VGG16—for classifying plant diseases. Notably, EfficientNetB5 exhibited superior performance, achieving a remarkable 99.2% classification accuracy.

Numerous studies have been carried out concerning the application of deep learning for disease identification in grape leaves.

The study [45] introduces an approach for grape leaf disease detection by utilizing convolutional capsule networks, which represent a promising neural network paradigm in deep learning. These networks use capsules, groups of neurons, to effectively capture spatial feature information. The novelty of this work lies in the inclusion of convolutional layers before the primary caps layer, reducing the number of capsules and expediting the dynamic routing process. The suggested approach, tested on both augmented and non-augmented datasets, successfully identifies grape leaf diseases with an impressive accuracy of 99.12%.

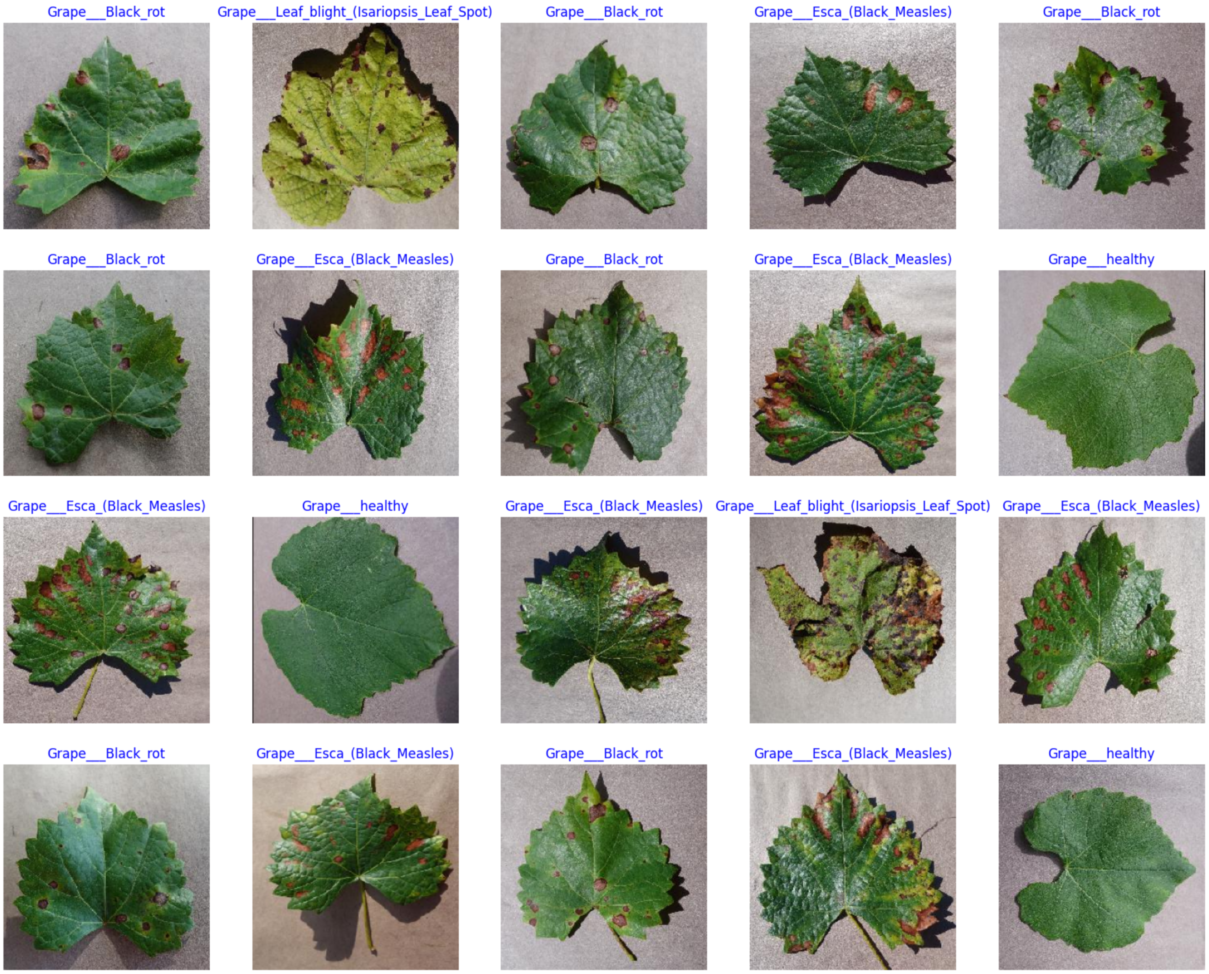
In this research [46], authors introduces the EfficientNet B0 deep learning model for the classification of grapevine leaves. The proposed deep learning architecture is compared with established counterparts, and the grapevine leaf dataset serves as the training data with 3000 images. The EfficientNet B0 model is trained through transfer learning and fine-tuning approaches, ultimately achieving the highest accuracy of 99.67%. This outperforms classical CNN and state-of-the-art models like VGG19, MobileNet V2, Inception V3, and ResNet152.

The study [47] delves into the classification of grapevine leaves using deep learning techniques. Initially, 500 pictures of vine leaves from 5 different species were captured using a specialized self-illuminating system, and this dataset was subsequently expanded to 2500 images through data augmentation. The classification process involved three methods: fine-tuning a state-of-the-art CNN model, MobileNetv2; obtaining features from the pre-trained Logits layer of MobileNetv2 and employing several SVM kernels; and selecting and reducing 1000 features from MobileNetv2's Logits layer to 250 using the Chi-Squares method, followed by classification with different SVM kernels. The most successful method involved feature extraction and reduction, with the Cubic SVM kernel achieving an impressive classification accuracy of 97.60%.

In [48], the study centers on the early identification and classification of grape diseases, introducing a novel framework that combines deep learning with conventional architecture for superior performance. The process involves three key steps: (a) feature extraction using transfer learning with pre-trained deep models like AlexNet and ResNet101, (b) feature selection employing the novel Yager Entropy and Kurtosis (YEaK) technique to identify the best features, and (c) merging these strong features using a parallel approach, followed by classification through least squared support vector machine (LS-SVM). The approach is validated through simulations on infected grape leaves from the plant village dataset, achieving an impressive accuracy of 99%. The results indicate the exceptional performance of the proposed approach in comparison to various existing methods.

In [49], the authors aimed to enhance grape leaf disease identification accuracy within constraints of limited computing resources and a small training dataset, utilizing deep transfer learning and an improved MobileNetV3 model named GLD-DTL. By retraining the modified networks using a grape leaf diseases dataset with six diseases constructed with data augmentation and image annotation techniques, the authors achieved exceptional results, with an identification accuracy of 99.84% and a compact model size of just 30 MB.

Highlighting the significance of proactive disease control, agricultural specialists and researchers persistently strive to innovate advanced technologies and techniques aimed at early disease detection, thereby enhancing the resilience and productivity of crop production systems worldwide. Therefore, the purpose of this study is to focus on the adoption of advanced technological solutions, including powerful pre-trained models like ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3. The study leverages these state-of-the-art techniques to achieve more precise and efficient classification of grape leaf diseases, ultimately strengthening disease management strategies. Furthermore, the research underscores the critical importance of fine-tuning model hyperparameters through extensive hyperparameter searches, using a hyperparameter optimization algorithm called Hyperband, a pivotal step in enhancing the predictive capabilities and overall effectiveness of the chosen model.


Grape___Black_rot
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Black_rot
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Grape___Esca_(Black_Measles)
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___healthy
Grape___Esca_(Black_Measles)
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Grape___Esca_(Black_Measles)
Grape___healthy

Fig. 1. Grape disease sample from the Grape Disease dataset.

III. Methodology

A. *Data Collection and Preparation*

In this study, we worked with a dataset comprising 9,027 images, sourced from Kaggle [50], known as the Grape Disease dataset. This dataset is divided into four classes: Grape-Esca-(Black-Measles) (Class 1), Grape-Black-rot (Class 2), Grape-Leaf-blight-(Isariopsis-Leaf-Spot) (Class 3), and Grape-healthy (Class 4). Sample images of grape diseases from this dataset are shown in Fig. 1, and the dataset distribution is visually represented in Fig. 2. Before proceeding with model training and evaluation, a preprocessing step is conducted on the images, which involves using an image preprocessing technique and sizing them to 224 x 224. The dataset is then divided into subsets, with 5,416 images allocated for the training set, 1,806 images for the validation set, and 1,805 images for the test set.

B. *Overall Methodology*

The research process can be divided into two primary phases.

1) Phase 1: Model selection and evaluation: The initial phase focuses on selecting the most suitable network architecture for classifying grape leaf diseases. This involves employing a transfer learning approach with established pre-trained models renowned for their performance. Rigorous evaluation criteria, including accuracy, F1 score, precision, recall, and loss, are used to assess these models. The objective here is to scientifically identify the model that performs best with the dataset (Fig. 3). Models used in this phase include: ResNet50V2 [51], ResNet152V2 [52], MobileNetV2 [53], Xception [54], and InceptionV3 [55].

2) Phase 2: Fine-tuning and hyper-parameter optimization: Following model selection, the next phase involves fine-tuning the chosen model's hyperparameters. This crucial step aims to improve the model's predictive abilities and overall effectiveness in identifying diseases. Extensive hyperparameter search utilizing the hyperband [56] strategy is conducted to refine and optimize the model's performance (Fig. 4).

The primary objective of hyperparameter optimization is to increase the efficiency and automate the hyperparameter tuning process. Unlike the model parameters (weights and

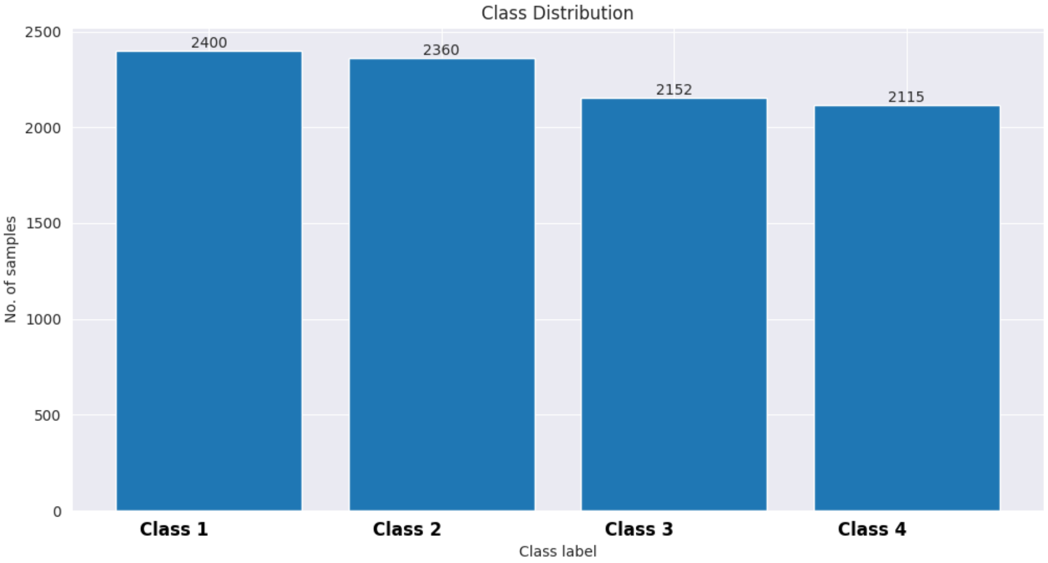

Fig. 2. A distribution of datasets.

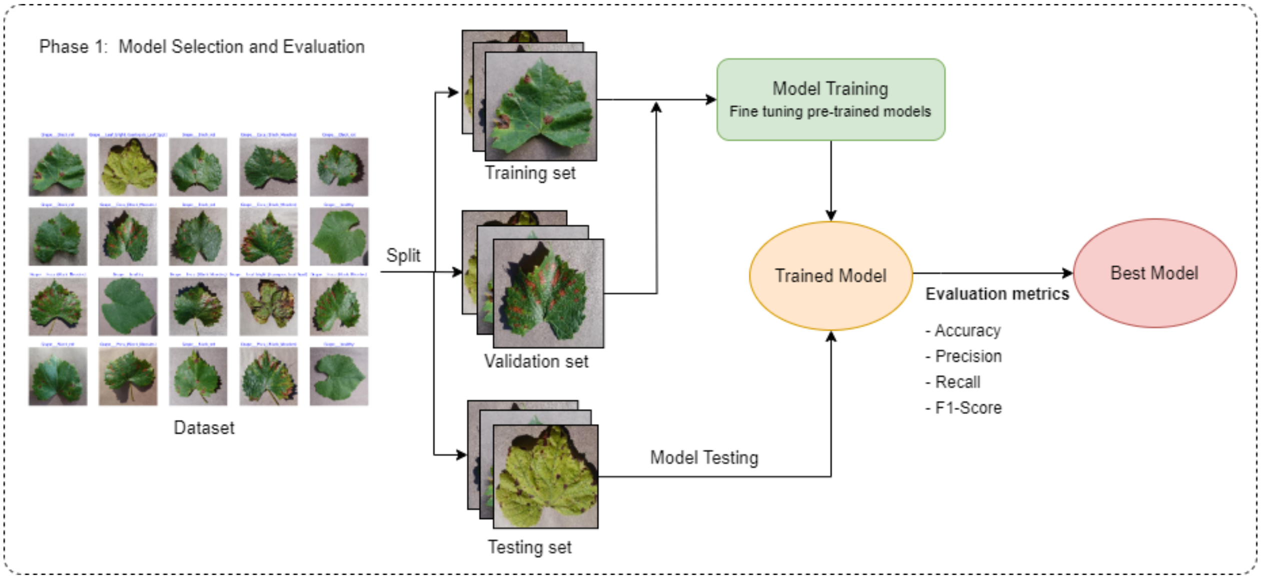

Fig. 3. The Process of model selection and evaluation.

biases), hyperparameters are set before the training begins and significantly influence the model's performance. The main goal is to find the most optimal set of hyperparameters that maximize the model's performance metrics. The ultimate goal of a hyperparameter optimization issues is to achieve Eq. (1).

$$x^* = \arg \underset{x\in X}{min} f(x) \tag{1}$$

Where $f(x)$ is the objective function; x^* represents the set of hyperparameter configurations that produce the best possible value for $f(x)$; The hyperparameter x can take on any value within the search space X.

C. Fine Tuning Pre-trained Models

In this research, the research team aim to employ a transfer learning methodology due to the scarcity of images depicting diseases on grape leaves. This approach offers substantial advantages in identifying crucial characteristics associated with grape leaf diseases. By utilizing trained models such as ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3, known for their high performance across diverse tasks, our goal is to determine the most suitable network architecture for our specific classification needs. These models will be adjusted before the training phase, keeping all of the original layer structure while adjusting the output using Batch Normalization layer. Additionally, they include a Global Aver-

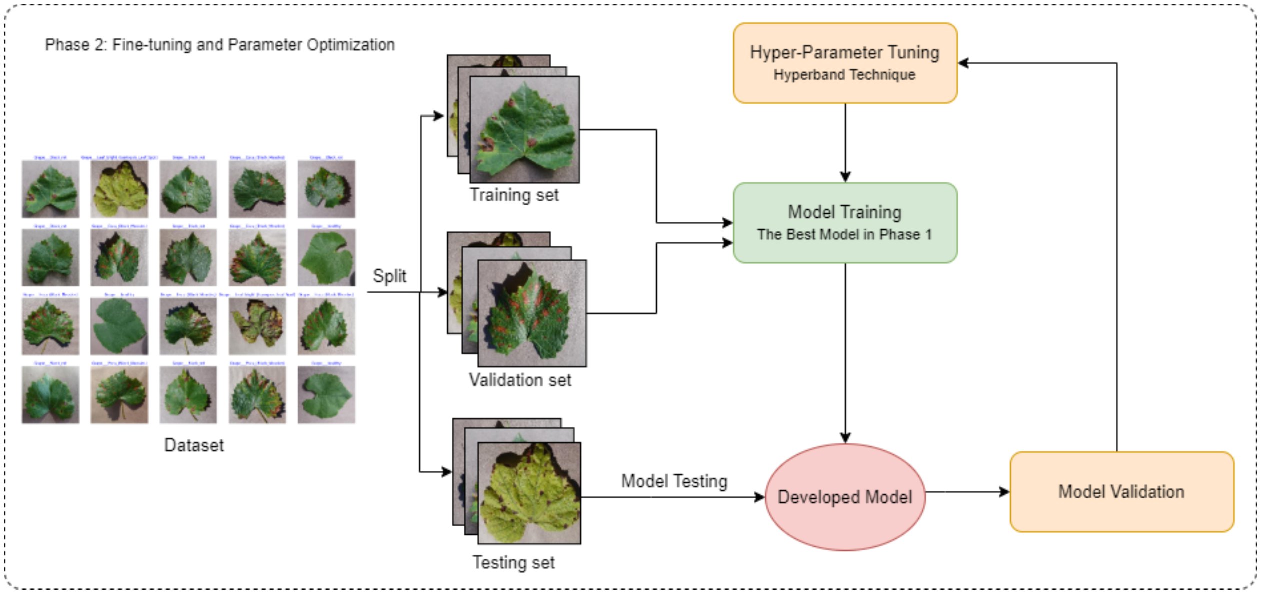

Fig. 4. The Process of fine-tuning and parameter optimization.

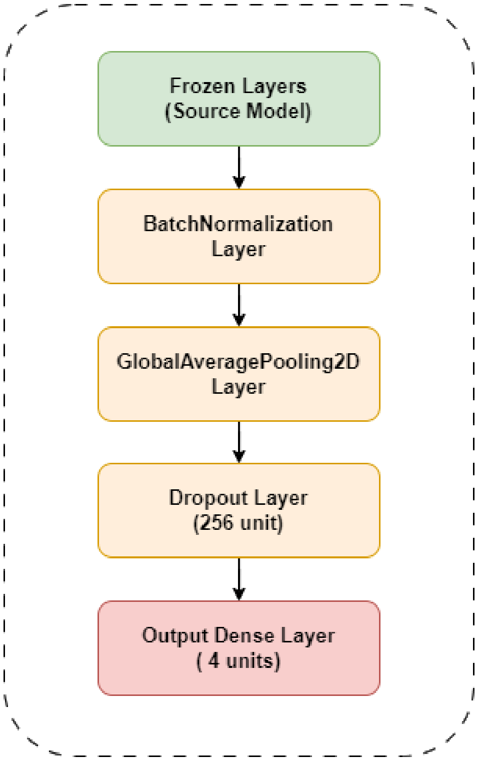

Fig. 5. Fine tuning pre-trained model.

age Pooling layer for spatial dimension reduction, a Dropout layer, a Dense layer featuring 256 units activated by ReLU, and finally, an output Dense layer with ’class count’ units employing softmax activation for classification purposes. Fig. 5 shows an overview of the fundamental structure of fine tuning pre-trained model.

D. Performance Evaluation Measures

The evaluation of the proposed model involved a comprehensive analysis using various key metrics. Precision, which measures the accuracy of positive predictions among all predicted positives, showcased the model’s capability to minimize misclassification of non-diseased instances in grape leaf disease classification. Recall, indicating the proportion of accurately predicted positives among all actual positives, highlighted the model’s effectiveness in identifying all relevant disease instances. The F1-score, derived from the harmonic mean of precision and recall, offered a balanced evaluation of how well the model balances precision and recall. Accuracy, a crucial metric in classification tasks, assessed the model’s ability to correctly predict instances overall within the dataset. Specifically in grape leaf disease recognition, accuracy indicated the model’s general correctness in identifying and categorizing various disease types from input grape images.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F_1 - Score = \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

In which, FP stands for False Positive, TN for True Negative, TP for True Positive, and FN for False Negative.

IV. Results

A. Environmental Settings

The experiments were carried out using the Kaggle platform in order to obtain the experimental results. The Tesla P100-PCIE GPU, which was employed in the research, had 16GB of memory, and the system had 13GB of RAM. The model was trained using a batch size of 32 over a duration of 30 epochs.

B. Experiment

1) Experiment 1: Model selection and evaluation: Table I displays performance metrics for various models. Among them, MobileNetV2 stands out with the highest accuracy of 97.00%, coupled with strong precision, recall, and an F1 score, all at 97.00%. Additionally, MobileNetV2 boasts the lowest loss value of 0.175 among the listed models.

This demonstrates that MobileNetV2 not only achieves the highest accuracy but also maintains the lowest loss, signifying robust overall performance and superior generalization compared to other models in this context. Therefore, MobileNetV2 remains in use for phase 2 to fine-tune hyperparameters and strengthen the model's robustness. Details on the Training/Validation Loss and Accuracy of the models in this study during training are presented in Fig. 6, Fig. 7, Fig. 8, Fig. 9, and Fig. 10.

TABLE I. The Fine-tuning Model's Testing Set Result

Models	Accuracy	Precision	Recall	F1 score	Loss
ResNet50V2	95.45%	96.00%	95.75%	95.75%	0.227
ResNet152V2	93.29%	93.50%	93.75%	93.50%	0.290
MobileNetV2	**97.00%**	**97.00%**	**97.00%**	**97.00%**	**0.175**
Xception	91.30%	91.75%	91.75%	91.50%	0.389
InceptionV3	89.19%	89.75%	89.75%	89.50%	0.415

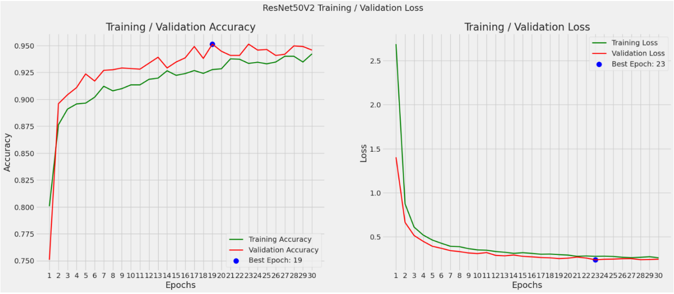

Fig. 6. ResNet50V2 training / validation accuracy and loss.

2) Experiment 2: Fine-tuning and hyper-parameter optimization: The search space for hyperparameters such as: Dropout rate, The number of units, Optimizer and Learning rate is given in Table II.

TABLE II. The Hyperparameter Search Space

The hyperparameters	Space for research
Dropout rate	Search space=[0.2, 0.3, 0.4, 0.5]
The number of units	Search space =[128, 256, 512, 1024]
Optimizer	Search space=['Adam', 'RMSprop', 'SGD', 'Adamax']
Learning rate	Search space=[1e-1, 1e-2, 1e-4, 1e-6]

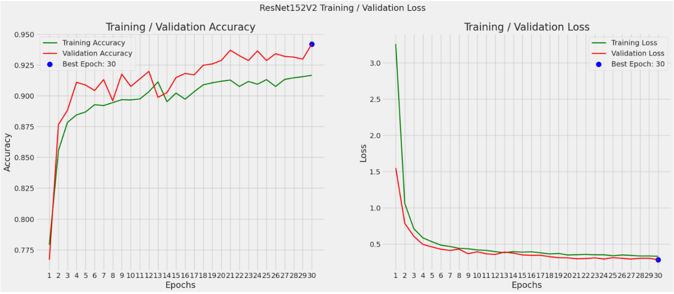

Fig. 7. ResNet152V2 training / validation accuracy and loss.

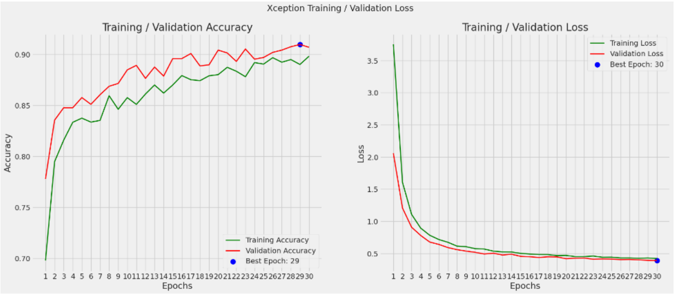

Fig. 8. Xception training / validation accuracy and loss.

After a thorough investigation of hyperparameters using Hyperband approaches and 45 trials, we achieved an outstanding 99.94% validation accuracy on the test set. The Test Loss that has been recorded is 0.144. Through careful tuning, the model was greatly improved, indicating an important improvement of 2.94%. The optimized hyperparameters, determined using Hyperband Optimization for fine-tuning the pre-trained MobileNetV2-based model, are presented in Table III.

TABLE III. Hyperparameter Values Found using Hyperband Optimization

Hyper parameter	Value
Dropout rate	0.4
Number of units	512
Optimizer	Adamax
Learning rate	0.0001

The best architectural model, obtained after determining the hyperparameter values, is shown in Fig. 11.

The presentation of Fig. 12 showcases a detailed comparison chart illustrating the performances of the best models concerning accuracy and loss scores.

And the confusion matrix of the best architectural model is shown in Fig. 13.

Table IV presents a comparative examination of the proposed model (the fine-tuned MobileNetV2-based model) with the state-of-the-art approaches on related issues. The table includes The plant's name, the number of disease labels, the number of pictures in the dataset, the detection method, and the accuracy rate.

According to research results, model proposed achieved a

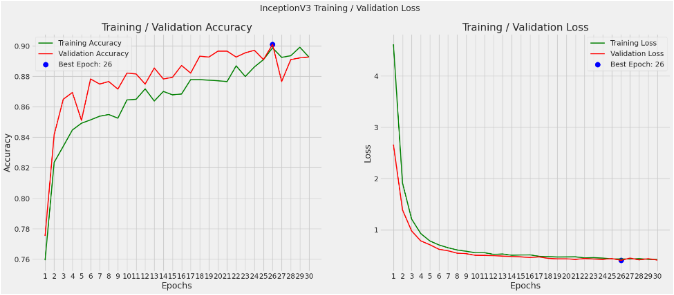

Fig. 9. InceptionV3 training / validation accuracy and loss.

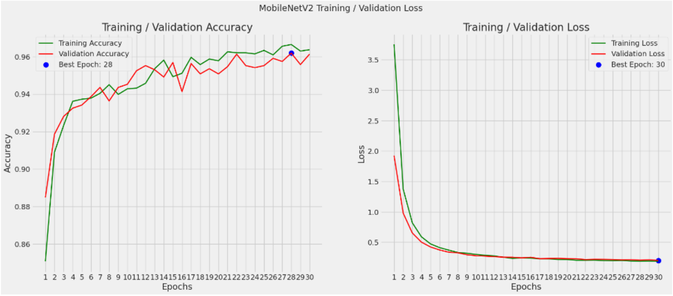

Fig. 10. MobileNetV2 training / validation accuracy and loss.

99.94% accuracy rate, outperforming all other techniques listed in the table for similar problems.

V. Conclusion

Growing grapes is an important worldwide enterprise that is essential for both nutritional value and economic survival. However, the quantity and quality of the crop are seriously threatened to a number of diseases. It is critical to identify these illnesses as soon as possible in order to maintain grape health and guarantee maximum yields.

To address this critical problem, we utilized a transfer learning approach that made use of a collection of reliable pre-trained models, including ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3. These deep learning models are known for their outstanding performance on a variety of tasks.

We carried an in-depth evaluation of these models, taking into consider a range of important metrics including as accuracy, F1 score, precision, recall, and loss. This comprehensive evaluation aims to determine which model performed the best given our particular dataset.

TABLE IV. Compare Current Approaches to our Suggested Model for a Similar Problem

Study	Dataset	No. Classes	No. Images	Method of Use	Accuracy
[57]	Soybean Diseases	4	12,673	CNN model	99.32%
[58]	PlantVillage's Apple Crop	4	2,086	VGG16	90.40%
[59]	Apple Leaf Disease	6	2,462	DenseNet-121	93.71%
[60]	PlantVillage' Tomato Leaves	7	13,262	AlexNet	97.49%
[61]	Apple Leaf Disease	9	1,100	MobileNetV2	96.23%
[62]	Tomato Leaves Diseases	9	14,828	GoogleNet	99.18%
[63]	The Tomato Plant	10	19,553	Inception-V3	99.75%
[46]	The grapevine leaves	5	3000	EfficientNet B0	99.67%
[64]	Grape Leaf Diseases	4	3,885	GoogleNet	94.05%
[65]	Grape Leaf Diseases	4	9,027	EfficientNet B7	98.70%
[47]	Grapevine Leaves	5	2,500	MobileNetv2	97.60%
This study	**Grape Leaf Diseases**	**4**	**9,027**	**Fine-tuned MobileNetV2-based model Hyperparameter optimization uses the Hyperband approach**	**99.94%**

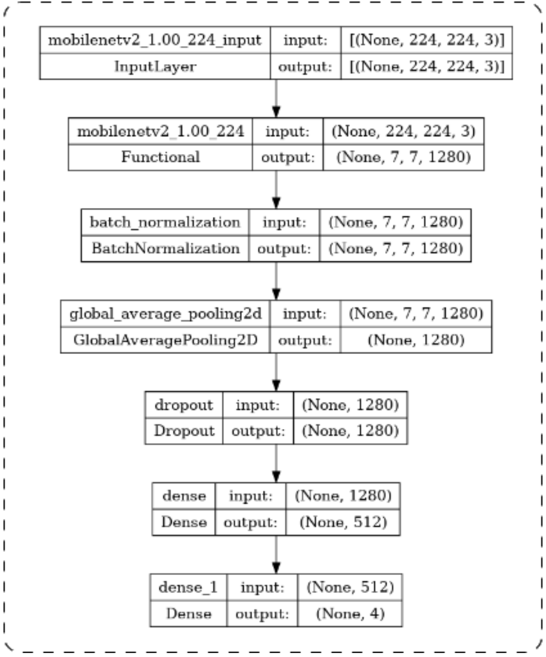

Fig. 11. The best architectural model, obtained after determining the hyperparameter values.

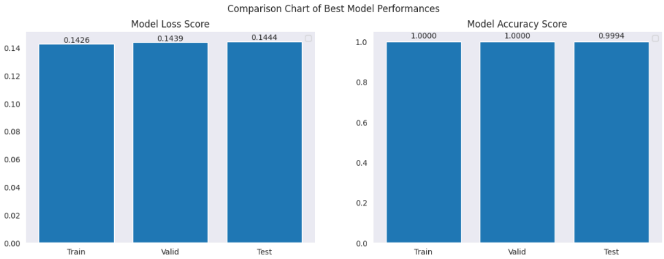

Fig. 12. Comparison chart of best model performances.

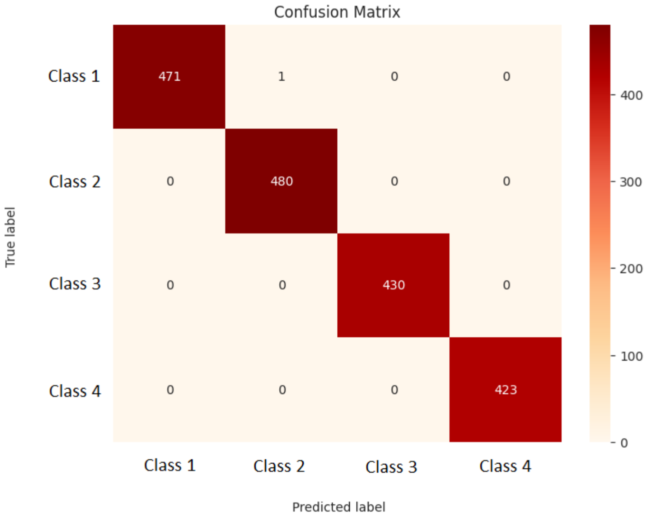

Fig. 13. The confusion matrix of the best architectural model.

We then moved on to the crucial step of fine-tuning the hyperparameters of the model that was performing at its best. This fundamental improvement process increases the model's overall efficacy in accurately recognizing grape leaf illnesses.

Our approach to fine-tuning involved an extensive exploration of hyperparameters using the hyperband strategy. This configuration was aimed at maximizing the model's performance specifically within the context of our dataset.

By using these careful procedures—model evaluation, selection, and refinement combined with carefully hyperparameter optimization, the model's accuracy on the test set was 99.94% and its loss was 0.1444.

VI. Future Works

Further investigations could explore into examining the influence of alternate hyperparameters based on optimization techniques—like weight decay, activation functions and batch sizes—aimed at enhancing the efficacy of transfer learning models in detecting grape leaf diseases.

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An Internet of Things-based Predictive Maintenance Architecture for Intensive Care Unit Ventilators

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***Abstract*—Intensive care units commonly utilize mechanical ventilators to treat patients with different medical conditions, which are crucial for patient care and survival. ICU ventilators have evolved through four distinct generations, each displaying unique features. Despite progress made since the 1940s, contemporary designs are insufficient to meet the increasing needs of patients and hospitals. Malfunctions in mechanical ventilators pose significant dangers to patients, highlighting the importance of focusing on their safety, security, precision, and dependability. Our study aims to address the significant issue at hand. Furthermore, the IoT industry has garnered significant attention because of rapid progress in smart devices, sensors, and actuators. The healthcare industry has seen a notable increase in health data as a result of the growing utilization of IoT and cloud computing technologies. To enhance growth, new models and distributed data analytics strategies must be developed to fully utilize the value of the vast datasets generated, including the incorporation of embedded machine learning. The study focuses on conducting Pareto and Failure Modes and Effects Analysis (FMECA) on ventilators in a specific hospital's ICU, specifically those manufactured by the same company and unit. The analysis aims to identify the most critical and failure-prone component. Subsequently, we propose an IoT-focused framework for a predictive maintenance system implemented at the component level. The architecture comprises a monitoring framework and a data analytics module to predict potential system failures in advance, enhancing overall reliability.**

Keywords*—Internet of things; predictive maintenance; embedded Machine learning; data analytics; failure modes; mechanical ventilator

I. Introduction

Nowadays, an average to large-sized hospital houses around 10,000 different types of medical devices, and one of the most pressing challenges for healthcare institutions throughout the world is to guarantee the safety of these devices and manage the risks connected with their use. Medical devices are tools or machinery used to detect, monitor, treat, or prevent illness or other disorders [1]. Providing health services through the use of diagnostic and therapeutic technologies is an essential component of health care, particularly in hospitals. In addition to being necessary for safe and effective patient care, medical equipment has a substantial impact on the income and consequently the viability of healthcare institutions [2]. Their rapid advancement has considerably benefited the health of individuals and society. This technological advancement has increased patients' survival in the face of sickness or injury, as well as considerably improved their life quality via improved diagnostic and therapy outcomes [3]. However, without effective maintenance management, the delivery of healthcare services to communities suffers dramatically. Medical equipment maintenance management is critical to ensuring that a machine performs by manufacturer specifications and ensures the safety of patients and users [4]. Inadequate maintenance of medical equipment causes downtime, reduces device performance, and wastes costs and resources. As a result, medical equipment requires both scheduled and unscheduled maintenance throughout its useful life and close monitoring by healthcare administrators [5]. Hospitals should ensure that medical equipment is kept in working order, is safe, accurate, and reliable, and functions at the appropriate level of performance successfully. Therefore, the ultimate goal of maintenance is reliability and safety. It should always be safe for both patients and users [6]. To that aim, the World Health Organization (WHO) specifies a standard regulation for periodic maintenance of medical devices that includes the rate of failure of specific types of replaceable components (e.g. batteries, valves, pumps, and seals) to assure device dependability and safety [7].

Thanks to digitalization in the healthcare domain, the generated health-related data have grown exponentially in the past decades with the increasing use of the Internet of Things (IoT) and cloud computing technologies in this field. As a result of this digitalization, a large volume of data is generated from these various IoT sources and information services. This motivates the health business to create new models and distributed data analytics approaches to maximize the value of the generated data [8]. In addition to this, advancements in information and communications technology, big data technologies, and analytics tools were the key elements in realizing the transition from traditional maintenance approaches to predictive maintenance (PdM) [9]. The IoT sector has attracted substantial interest due to the rapid pace of technical breakthroughs in smart device, sensor, and actuator technologies. A multitude of these IoT devices can potentially generate significant amounts of big-data streams which are not only too voluminous but also too fast and complex to be processed and stored using traditional data analytics approaches. Therefore, predictive maintenance systems should be highly scalable, resilient, and fault-tolerant to process and store big data in an effective manner [10]. Through the use of information and communication technologies, specifically intelligent devices (such as IoT sensors, edge devices, and computing), data collection has increased as a result of the incorporation of autonomous and smart systems where data and advanced data analytics (i.e., big data, artificial intelligence (AI) / Machine Learning (ML)) can be used [11]. With this development, PdM solutions, such as those for estimating remaining usable life, detecting anomalies, and monitoring machine health (condition), also increased. PdM entails making optimum decisions to sustain a system's capacity and functioning by monitoring its performance in real-time using huge data streams provided by the system. The use of predictive maintenance approaches enables us to reduce operational maintenance costs for medical devices, enhance operational activity without breakdowns, and thereby improve healthcare quality.

In other words, PdM is described as a set of procedures used to assess the state of equipment and predict future failures. These estimations are then utilized to schedule maintenance activities through smart scheduling of maintenance procedures, which aids in preventing or at least minimizing the impacts of unanticipated breakdowns. PdM requires employing analytical tools to analyze machine-generated data to get valuable insights. Further, create a machine learning (ML) model using this data to forecast upcoming failures. Sensors with limited data processing capabilities are used for data collecting. Due to this, edge devices were developed and are now capable of processing data, cleansing data, and many other functions in addition to acting as sensors [12]. PdM techniques are very similar to medical diagnostic techniques. A symptom appears whenever a human body is experiencing a problem. The information is provided by the nervous system; this is the detection stage. Pathological tests are also performed if necessary, to diagnose the problem. On this basis, appropriate treatment is suggested. Similarly, defects in a machine always produce a symptom in the form of vibration or some other parameter. However, on machinery systems with human perceptions, this may or may not be easily detected.

The rest of the paper is organized as follows; in Section II, the maintenance strategies are described and the related works are reviewed. Section III describes the functioning of the mechanical ventilator. Section IV addresses the study case and discusses the proposed architecture for predictive maintenance in the big-data era. The opportunities and challenges of the proposed architecture are discussed in Section V. We conclude paper and give directions for future research in Section VI.

II. Background and Related Works

A. Background

In light of the technological advances in the medical field, medical equipment has become widely used in all aspects of health care, including prevention, screening, diagnosis, monitoring, and therapeutics, as well as rehabilitation. It is now nearly impossible to provide health care without them. Medical equipment, unlike other types of healthcare technologies (such as drugs, implants, and disposable products), requires maintenance (both scheduled and unscheduled) throughout its useful life. Inadequate and improper maintenance and safety procedures have always been the leading cause of major incidents frequently involving patients that result in serious injuries or deaths.

Maintenance can be defined as the function of keeping a machine, or system (whether simple or complex) in working order by using it properly, repairing broken parts or components, or replacing some of the broken parts so that it is available and fit for the intended purpose whenever the need arises. A maintenance strategy is a methodical approach to device upkeep that includes actions like ”identification, investigations, and execution of many repairs, replace, and inspect decisions”. According to [13] a maintenance strategy includes a set of policies and actions that are used to “retain” or “restore” equipment as well as the decision support system in which maintenance activities are planned. As the sophistication and cost of medical equipment have increased, so has the complexity and cost of its maintenance over the last few decades.

Maintenance philosophy has always evolved in pari-passu with the ever-changing technological innovations in designing simple machines and equipment that have now metamorphosed into complex, sophisticated, and indispensable systems. Maintenance strategies have evolved gradually, and the process is still ongoing. Over the last two decades, maintenance strategies and reliability engineering techniques have been significantly improved, and they have been successfully applied in many industries to improve the performance of equipment maintenance and management. Maintenance strategies can be categorized as first, second, third, and recent generations, as depicted in Fig. 1.

Corrective maintenance (CM) [14] is a reactive maintenance policy that is applied following a machine malfunction. The following sentence serves as the foundation for the concept of corrective maintenance: Fix it when it breaks. CM is classified as first generation as it was the standard practice until the 1960s when preventive maintenance (PM) concepts emerged and gained public recognition.

PM [15] categorized as second generation, entails inspecting and maintaining equipment while it is in operation to reduce the likelihood of a breakdown. Preventive maintenance can be scheduled in advance (time-based schedule) or as needed (usage-based schedule). While this strategy reduces failures thus improving equipment efficiency, reducing downtime, and extending the life of your equipment by ensuring it is always in good working order. The issue with the PM strategy is that it can be excessively proactive. Because you are following a standard timetable, you can schedule a part replacement well in advance of when it is required. This will increase the cost of maintenance.

Condition-based maintenance (CBM) [16] classified as third generation, emerged in the second half of the 1980s as a result of sensor and condition monitoring technology development. To reduce unnecessary scheduled tasks, this strategy limits the number of times maintenance activities are initiated to when there is clear evidence of deterioration. Monitoring the condition of the equipment and performing necessary maintenance are all part of CBM. When compared to preventive maintenance, there is no need to be concerned about performing condition-based maintenance too soon. When something goes wrong but before it stops working, sensors notify you that maintenance is required at the optimal time. Condition-based maintenance is also known as condition-based monitoring because it requires regular monitoring of your equipment. The major drawback is that you can't plan for maintenance because you won't realize you need it until the changes happen.

The concept of prognostics, which deals with fault prediction before it occurs, was recently introduced to the proactive maintenance community in recent years. In this context, PdM [17] is a CBM policy that incorporates prognostics into its decision-making process. As a result, PdM contains more information about asset degradation, such as the remaining useful life (RUL). PdM represents the recent generation of maintenance philosophies.

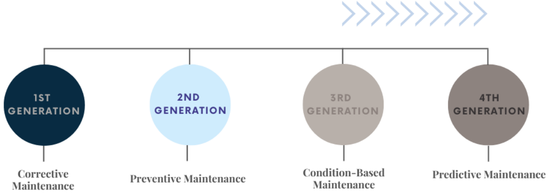

Fig. 1. Evolution through time of maintenance strategies.

B. Related Works

Several articles in the literature propose a system architecture for predictive maintenance in the healthcare domain. Two different architectures for PdM systems were proposed in 2013. D. Andriţoi, C. Luca, C. Corciovă, and R. Ciorap, have developed a novel application with a robust evaluative facility. Using the medical equipment maintenance records stored in this application's database, a mathematical model for predictive maintenance can be developed [18]. A second method was proposed by M. Ullrich, K. Ten Hagen, and J. Lässig, who described a new approach for categorizing maintenance visits according to PdM [19]. To enhance medical device decision-making, the following study [20] details a comprehensive PdM management system that makes use of Information and Communication Technologies (ICT) and predictive analysis tools. This paper [21] proposes the following guidelines for a PdM model: It is important to 1) conduct daily QA treatment; 2) transfer and automatically interrogate the resulting log files; 3) analyze daily operating and performance values using statistical process control (SPC) once baselines are established; 4) determine if any alarms have been triggered; and 5) notify facility and system service engineers. A significant part of this research involved the development of software modules to automate the interrogation of trajectory log files, perform the SPC evaluation, and display the results in a graphical dashboard interface.

In 2018, [22] and [8] outline a PdM architecture for medical devices that makes use of modern big data, cloud, and IoT technologies. The following work [23] also delves into the challenge of healthcare organizations' maintenance by examining an autonomous integrity monitoring approach for devices that transmit massive amounts of real-time data via the Internet of Things. By combining an integrity monitoring framework with a data analytics module, the proposed architecture provides full visibility into medical devices and permits the anticipation of future problems.

In [24] a theoretical design employing Internet of Things technology is proposed. Furthermore, infrared cameras, such as those used for infrared thermal imaging, which have the incredible capacity to observe things that conventional diagnostic instruments cannot, are proposed as an effective tool for PdM strategy in the following paper [25]. Finally, [26] proposes a methodology that takes into account data sets, features, evaluation strategies, prediction strategies, ML algorithms, and performance evaluation.

III. Mechanical Ventilator

A. Evolution of Mechanical Ventilator

A mechanical ventilator is a device that facilitates or replaces spontaneous breathing, it aids in respiration or takes breaths for the patient. Mechanical ventilation is lifesaving when natural breathing is ineffective or has ceased. The patient's ventilation is increased by the ventilator, which fills their lungs with oxygen or air and oxygen. Mechanical ventilators have made significant advancements since their introduction, in addition to their use in the intensive care unit (ICU), Mechanical ventilators have many applications inside and outside of hospitals. Ventilators are crucial in the management of patients undergoing general anesthesia inside the operating room, in patients' homes for extended treatment, and the transporting vehicles. This was accomplished by combining advances in our understanding of respiratory physiology, pathophysiology, and clinical patient management with technological advancements in mechanical, electronic, and biomedical engineering. New devices and an increasing number of ventilation modes and strategies are introduced to improve outcomes, patient–ventilator interactions, and patient care in the present day. The primary indication for mechanical ventilation is difficulty in the patient's ventilation and/or oxygenation due to any respiratory or other condition. The objectives of mechanical ventilation are to provide adequate oxygen to patients with a limited vital capacity, to treat ventilatory failure, to reduce dyspnea, and to allow breathing muscles to relax. There are two types of ventilation: Positive pressure ventilation (PPV) involves forcing air into the lungs through the airways, while negative pressure ventilation (NPV) involves drawing air into the lungs.

The use of assisted ventilation dates back to biblical times. In the early 1800s, however, mechanical ventilators in the form of NPV first appeared. The negative-pressure ventilator was the standard method of providing respiratory support throughout the latter half of the 19th century and the first half of the 20th. These devices were capable of applying alternating subatmospheric pressure around the body and were used to restore ventilation in patients by expanding the chest wall. The initial description of a negative pressure ventilator involved a full-body ventilator. In 1838, the "tank ventilator" was described for the first time by the Scottish physician John Dalziel. It consisted of an airtight box in which the patient was held in a seated position. By manually pumping air into and out of the container, negative pressure was created.

Sauerbrach even created a negative-pressure operating chamber in 1904. Except for the head, the patient's body was maintained within the chamber. Numerous other types of negative-pressure chambers, such as the "raincoat" and the "chest cuirass," were developed and used with varying degrees of success over time.

In the 1960s, however, there was a shift away from negative-pressure ventilation due to several factors. For example, access to the patient was limited, and "tank shock" was a recurring problem with full-body ventilators. However, mechanical ventilation became widespread only after the introduction of positive-pressure ventilation during the resurgence of poliomyelitis in the 1950s. This global pandemic has limited the availability of cabinet ventilators. To overcome this challenge, Bjorn Ibsen, a Danish anesthesiologist, utilized a modified anesthetic circuit with a squeezed bag to provide intermittent positive pressure ventilation (IPPV).This demonstrated a dramatic reduction in mortality in patients manually ventilated via tracheostomy led to the development of the intensive care unit.

In 1940, the first positive-pressure mechanical ventilators became commercially available. Even though they possessed a high level of sophistication, they could only deliver a predetermined tidal volume at a given respiratory rate (volume-control ventilation mode) and had no or very limited monitoring capabilities for ventilation variables.

The field of respiratory physiology had already established its foundations and was expanding rapidly at the time. In 1903, Dixon and Brodie introduced the application of mathematical modeling to describe the relationships between flow and pressure, which marked the beginning of the mechanics of breathing. They modeled the lung as resistance and compliance. In 1946, Rahn et al. presented pressure–volume diagrams of the lung and thorax as well as the concept of relaxation curves, laying the groundwork for the development of respiratory energetics. These and other studies provided the physiological foundation that led to the clinical application of positive-pressure ventilation.

Beginning in the early 1970s, ventilators began incorporating more advanced monitoring of flow and pressure variables due to advances in electronics. Improvements in monitoring also permitted the use of real-time variables to control the action of the machine, with the intermittent mandatory ventilation mode paving the way for the development of assisted mechanical ventilation as a means to wean patients from volume-controlled ventilation.

Beginning in the early 1980s, the introduction of microprocessors in mechanical ventilators led to the introduction of improved technologies for monitoring ventilation and lung conditions, as well as the introduction of new, advanced ventilation modes.

From the original ventilators of the 1940s to the present day, there have been four generations of ICU ventilators, each with features distinct from the previous generation.

B. Operation Principle of Mechanical Ventilator

Mechanical ventilation (MV) functions by applying a positive pressure breath and is dependent on the airway system's compliance and resistance. During spontaneous inspiration, the lung expands as transpulmonary pressure (P) is primarily generated by the inspiratory muscles' negative pleural pressure. During controlled mechanical ventilation, on the other hand, a positive airway pressure forces gas into the lungs, resulting in a positive P. The tidal volume (VT) is the volume of air that enters or leaves the lungs during each respiratory cycle. Physiologically, VT is dependent on a person's height and gender and ranges from 8 to 10 mL/kg of ideal body weight. Multiple modes of MV delivery exist, including mandatory mode and assisted mode. In the assisted mode, the patient's inspiratory effort activates the MV to deliver the breath, while P is the product of negative pleural pressure and positive alveolar pressure. The most prevalent modes of MV include: Volume-limited assist control ventilation (VAC), Pressure-limited assist control ventilation (PAC), and Synchronized intermittent mandatory ventilation with pressure support ventilation (SIMV-PSV).

Once a ventilation strategy has been determined, it should be administered to the patient in the most precise manner possible. To accomplish this, the machine must accurately detect all variables that define the breathing pattern and adapt its action in real-time. Modern ventilators accomplish this by combining sophisticated data processing algorithms with cutting-edge actuators, sensors, and digital electronics.

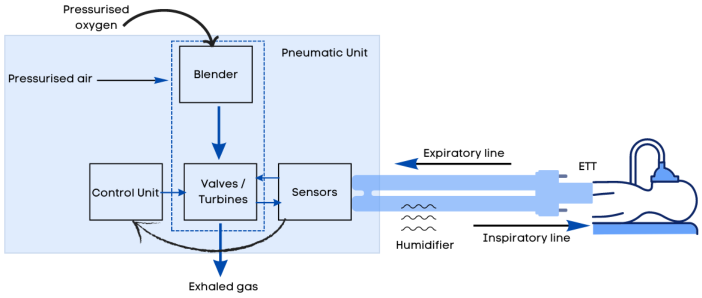

Fig. 2. Representative illustration of the mechanical ventilator functioning.

Fig. 2 depicts a representative illustration of the mechanical ventilator functioning, with the operation principle including:

1) Pneumatic unit: The pressure source provides the energy necessary to overcome the elastic and resistive load imposed by the patient's respiratory system and is used to reduce the patient's work of breathing. The pressurized air is mixed with the appropriate amount of oxygen by the blender and delivered to the patient through fast valves that modulate the amount of gas flowing into and out of the patient. In some modern ventilators, instead of using valves, a fast-response, brushless-driven turbine functions as a variable pressurized air source, making the device independent of centralized medical compressed air distribution while still delivering excellent performance.

2) Sensors: In contemporary mechanical ventilators, all relevant ventilation parameters like pressure, flow, and F_iO_2(The fraction of oxygen in the inspired air or gas that is being provided from a ventilator) are measured by sensors that provide information to the control unit so that the valves/turbines can be adjusted in real time to deliver the desired ventilation mode.

IV. Study Case : CARESCAPE R860

A. Objective

The ICU ventilator is characterized by its long-term use. Indeed, it must be able to act continuously on the same patient for multiple days. Any ICU ventilator malfunction has the potential to be catastrophic and fatal for patients. Despite the presence of alarm systems, continuous monitoring is required to minimize machine-related errors. Therefore, this study aims to propose an IoT-based architecture for predictive maintenance of the CARESCAPE R860 ICU ventilators.

The primary objective of our architecture surpasses the limitations of a single healthcare facility. The objective of this study is to establish the potential for widespread implementation of the suggested approach on CARESCAPE R860 ICU ventilators within a wide range of healthcare institutions. To establish a comprehensive and adaptable predictive maintenance (PdM) system, our objective is to develop a flexible framework that can effectively accommodate diverse hospital structures. This endeavor is driven by the goal of establishing a centralized approach that effectively harmonizes with a multitude of healthcare settings.

This study was conducted on a collection of CARESCAPE R860 ICU ventilators located in various medical centers.

B. General Description of the CARESCAPE R860

The CARESCAPE R860 is a sophisticated ICU ventilator that integrates modern technology with a user-friendly interface, as shown in Fig. 3. The icons in the interface reflect customizable depictions of historical patterns, patient status, and clinical decision assistance for future patient needs. The ventilator includes a display, ventilator unit, trolley with optional AC plug, optional EVair compressor, and module bay with optional gas module.

Users have complete control over the system setting due to the wide range of performance options provided. This comprehensive ventilator system includes breathing, monitoring, and the ability to connect with central monitoring systems. The user-friendly touch screen allows quick and easy access to information and operations, catering to adult, pediatric, and neonatal patients.

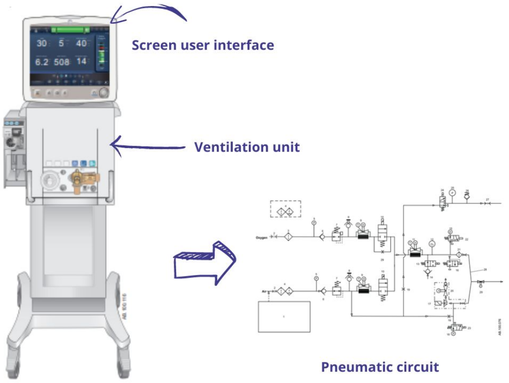

Fig. 3. Overview of the ICU ventilator.

1) Screen user interface: The interactive panel screen displays the patient's and ventilator's current status. Even during normal ventilation, all modes, controller, alarm, and monitoring windows are accessible directly from the main screen. The menu, the menu for the current patient, alarm management, and the user's favorite procedures are grouped at the top of the screen in the user interface. The status of the patient (the airway pressure bar) and the workspace/monitoring area are located in the center of the display. At the bottom of the screen are the navigation bar, message areas, battery status, standby button, and shortcut keys.

2) Ventilation unit: The ventilation unit is located on the front of the ICU ventilator, below the screen user interface, and is equipped with all the necessary ports for connecting the various breathing circuit accessories.

3) Pneumatic circuit: The pneumatic circuit of the ventilator provides patient gases from compressed air and oxygen sources. Two distinct inspiratory channels (air and O_2) are incorporated into the system to provide dynamic O2 percentage mixing control.

4) Electronic circuit: The electronic unit contains the various electronic circuits used to control and adjust the pneumatic system, the monitoring represented by the ventilator's alarm set, and the machine user interface.

C. Pareto Analysis for the CARESCAPE R860

The ABC method or Pareto analysis permits the analysis of the most significant malfunctions. It enables us to assert that 20% of the causes are accountable for 80% of the problems encountered and, as a result, to analyze all of the problems in order to formulate an appropriate response.

In our case, we have performed a Pareto analysis on different CARESCAPE R860 ventilators from the same unit. This method will allow us to identify the CARESCAPE R860 component that is most failing.

The Pareto analysis is accomplished by following the steps outlined below:

- Step 1: Sort the failures according to the number of failures in descending order
- Step 2: Determine the percentage
- Step 3: Determine the cumulative percentage
- Step 4: Draw the curve and identify the three zones: A, B, C

Fig. 4 depicts the outcomes of the Pareto analysis of a CARESCAPE R860. The curve illustrates a convexity with the selection of three zones; each zone contains a certain number of components in proportion to the significance of their total number of breakdowns; the following are the three zones that I discovered:

1) Zone A: Highest risk area. 80% of the risks originate from the five following components and processes:

⇒ Changing the air block

⇒ Changing the backup batteries

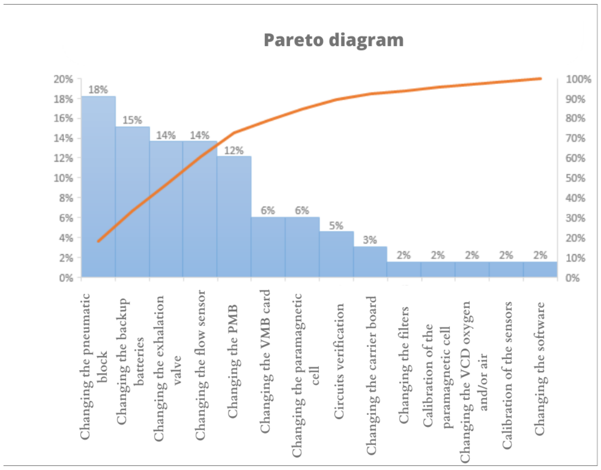

Fig. 4. Pareto analysis of a CARESCAPE R860.

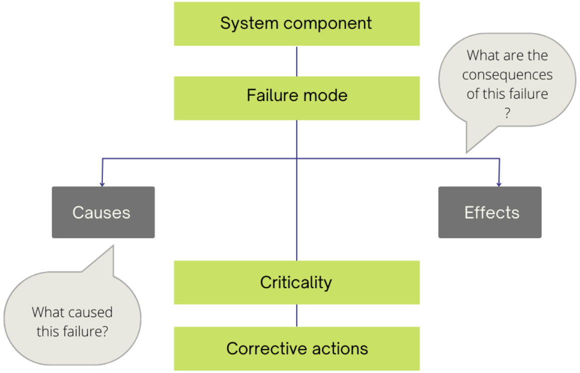

Fig. 5. FMECA analysis of the system.

⇒ Changing the exhalation valve

⇒ Changing the flow sensor

This means that we will be concentrating our solution-finding efforts on these parts, as their failure would have the most severe consequences.

2) Zone B: Medium risk area. 15% of the risks are caused by the following five parts or procedures:

⇒ Changing the PMB

⇒ Changing the VMB card

⇒ Changing the paramagnetic cell

⇒ Circuits verification

⇒ Changing the carrier board

3) Zone C: Low risk area. 5% of the risks are caused by the following parts or procedures:

⇒ Changing the filters

⇒ Calibration of the paramagnetic cell

⇒ Changing the VCD oxygen and/or air

⇒ Calibration of the sensors

⇒ Changing the software

After conducting this analysis on the different CARESCAPE R860, it has revealed that all ICU ventilators have the same pneumatic block issue.

D. Develop a Failure Mode and Effects Analysis for the CARESCAPE R860

To conduct this investigation, we also performed a Failure Mode and Effects Analysis (FMEA), also known as a Failure Mode, Effects, and Criticality Analysis (FMECA), on the selected equipment. The FMECA is a technique for predictive analysis that estimates the risks of failure and their effects on the equipment's proper operation and then implements the necessary corrective actions. Its primary objective is to maximize availability. This analysis will allow us to determine which component of the machine is the most critical and malfunctioning in our scenario.

The FMEA method is based on a multi-step process as shown in Fig. 5. The different steps are described as follows:

1) Identify possible failures and their effects: This step involves identifying all potential failure modes, determining the effects of each, and searching for their most probable causes.

2) Determine Gravity (G): The gravity G represents the severity of the effects of a failure. G is rated on a scale from 0 to 4, with 0 being the least severe and 4 being the most severe.

3) Determine the occurrence frequency (F): The frequency of occurrence F represents the failure occurrence frequency. This frequency represents the probability of the failure mode occurring in conjunction with the failure cause. F is rated on a scale from 0 to 4, where 0 represents the probability that a failure is practically impossible to occur and 4 represents the certainty of a failure occurring.

4) Failure detection (D): Detection mode D refers to the likelihood that a user will detect the occurrence of a failure. Detectability is a crucial component. Failure to predict a failure will increase the likelihood that the system will shut down. D is rated on a scale from 0 to 4, where 0 indicates the presence of sensors capable of detecting the onset of a failure and 4 indicates that the malfunction is undetectable or that its location requires extensive knowledge.

5) The criticality evaluation (C): Criticality is a quantitative evaluation of risk based on the combination of the three previously mentioned factors:

⇒ The frequency with which the mode-cause pair occurs.

⇒ The severity of the effect.

⇒ The possibility of employing detection methods.

Calculated using the formula $C = G \times F \times D$, it is intended to assess the risk associated with equipment functionality.

We have divided criticality into four categories:

→ Level A: Negligible criticality

→ Level B: Medium criticality

→ Level C: High criticality

→ Level D: Very high criticality

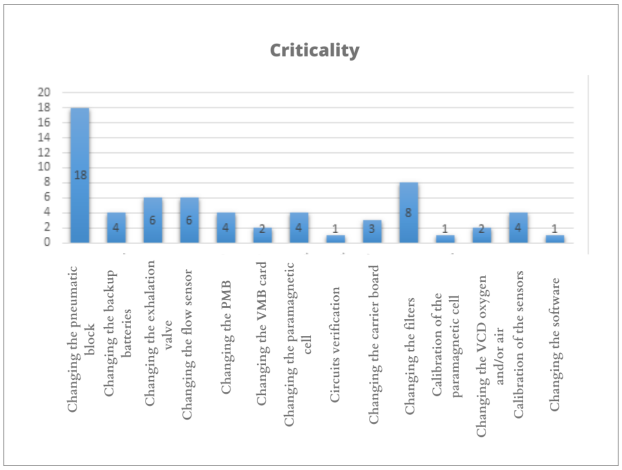

Fig. 6. Criticality Rate Diagram based on the number of failures.

After identifying the various potential failures that the ICU ventilators may encounter during their operation, we analyzed and investigated the effects of these failures on the CARESCAPE R860's proper operation, the user, the patient, and the environment. We then determined for each failure the three previously mentioned parameters, namely severity, occurrence frequency, and mode of detection, in order to calculate the criticality of each failure. Fig. 6 illustrates the results of the FMECA analysis.

With a criticality of C=18, we can conclude that the pneumatic block is the ICU ventilator's most critical component. If the pneumatic block fails, this can directly result in an outage of our ventilators, which can alter the patient's course of treatment or be fatal.

E. Proposed Architecture

Following our primary objective of achieving centralization, the architectural framework we have developed is intricately connected with the knowledge acquired through our extensive research. The present investigation was carried out with a specific emphasis on intensive care unit (ICU) ventilators, with particular attention given to the CARESCAPE R860 model. The study was conducted within a single hospital unit, aiming to achieve a comprehensive comprehension of the challenges associated with this particular model. The present study employed the Pareto and Failure Modes and Effects Analysis (FMECA) methodologies to conduct an analysis, thereby facilitating the identification of the critical parameters and components that exhibit a higher susceptibility to failure.

Patients are put in an intolerable position of risk when their mechanical ventilators malfunction, so ensuring the safety of these devices is crucial [27]. It is more cost-effective to perform preventative maintenance on the mechanical ventilators rather than repair work on them. An organization or a person with expertise in technical installations is required to perform continuous monitoring and maintenance on the air unit that serves as the source of air for both the ICU service and the neonatology service. The performance of the installation is something that must be guaranteed, which is why maintenance is performed. The following are the components of maintenance:

→ Ensure that optimal filtration is maintained at all times by performing follow-up and monitoring of filtration. Regularly dispose of and replace filters.

→ Perform routine maintenance on the motor-fan assembly in order to ensure consistent flow rates.

→ Ensure that power plants are kept clean in order to preserve the quality of the air.

→ Ensure that all of the electrical, regulatory, and safety equipment is in proper working order (antifreeze thermostat, smoke detection, etc.)

It is necessary to ensure that the maintenance actions implemented have been properly carried out. As a result, the system ought to be monitored in a manner that is both sustainable and capable of ensuring that the ventilators continue to function normally without exhibiting any signs of performance degradation. As a result, we propose incorporating a humidity monitoring system at the chain level of the medical air filtration process. Consequently, we propose an IoT-based architecture for predictive maintenance that collects and processes a massive data stream from several CARESCAPE R860 in real-time.

Our proposed structure comprises four layers (Fig. 7):

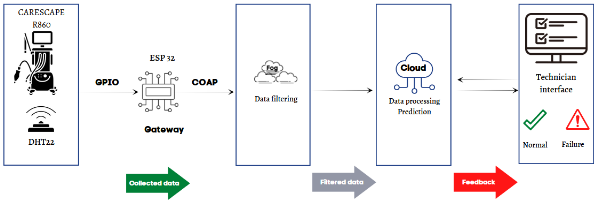

Fig. 7. Proposed architecture for the CARESCAPE R860.

1) The first layer: The first layer is the input layer. It is composed of a humidity and temperature sensor known as DHT22 which is an inexpensive digital temperature and humidity sensor. Using a capacitive humidity sensor and a thermistor, it monitors airflow and outputs a digital signal on the data pin. It sends information every two seconds. The DTH22 will be installed in the air filtration chain of the machine in order to monitor the performance of the pneumatic block. The data, which consists of the measured humidity levels at a variety of time intervals, will be transmitted to the fog through the Constrained Application Protocol (CoAP) by utilizing the ESP32 microcontroller as a gateway.

2) The second layer: The second layer within our Predictive Maintenance (PdM) framework is an essential element referred to as the fog computing layer. The present layer is strategically situated in the intermediary position between the peripheral devices, specifically the ventilators equipped with DHT22 sensors that are deployed across various hospital services, and the centralized cloud server. The principal aim of integrating the fog computing layer is to augment the efficacy, responsiveness, and scalability of our predictive maintenance system.

a) Centralized data processing and filtering: In the context of fog computing, the data coming from the distributed ventilators is gathered, subjected to real-time processing, and subsequently filtered. The adoption of a decentralized approach in information processing has been shown to have significant benefits in terms of reducing latency and facilitating prompt analysis of critical information within local networks. This approach effectively minimizes the dependence on distant cloud servers for immediate decision-making purposes.

b) Local anomaly detection and classification: The utilization of fog computing technology facilitates the implementation of localized anomaly detection and classification algorithms, thereby facilitating the rapid identification of potential issues that are unique to each ventilator system. The presence of localized intelligence plays a crucial role in effectively addressing immediate concerns and mitigating the negative impacts of faults on patient care. The fog layer functions as a discerning filter, selectively transmitting solely pertinent and practicable data to the central cloud server.

c) Bandwidth optimization: In light of the limitations imposed by bandwidth constraints and the unpredictable nature of network conditions, the fog layer exhibits intelligent behavior in order to optimize the transmission of data. The proposed system effectively employs a filtering mechanism to eliminate redundant or non-critical information, thereby significantly reducing the overall volume of data that necessitates transmission to the cloud. The optimization of system efficiency is not only observed but also found to be positively correlated with cost savings in the context of data transfer and storage.

d) Edge machine learning for quick decision-making: The utilization of machine learning models implemented at the fog layer significantly contributes to the facilitating of localized decision-making processes. These models are trained on historical data and regularly updated to promptly detect patterns and trends related to potential malfunctions in ventilators. The significance of localized intelligence becomes especially apparent in situations necessitating prompt intervention to prevent detrimental impacts on patient well-being.

e) Scalability and interoperability: The integration of ventilators from various hospital services is facilitated by the fog computing layer, ensuring a seamless and efficient process. The proposed solution offers a scalable and interoperable framework, thereby enabling the predictive maintenance system to effectively adapt to diverse ventilator models and configurations. The establishment of interoperability within the healthcare sector is of the highest priority to facilitate extensive acceptance and utilization across diverse healthcare facilities.

f) Centralization objective: The primary objective of incorporating fog computing within our predictive maintenance architecture is to establish a centralized framework for managing predictive maintenance operations associated with a diverse range of ventilators sourced from multiple services and hospitals. The process of centralization facilitates the efficient management of operations, and maintenance of algorithms, and offers a comprehensive assessment of ventilator performance within the hospital network.

In this study, we propose a novel approach to enhance the utilization of computing resources and facilitate effective coordination of predictive maintenance operations by implementing a centralized management system through the fog. The fog computing paradigm is leveraged to achieve these objectives. By adopting this approach, we aim to optimize the allocation and utilization of computing resources, thereby improving the overall efficiency of predictive maintenance operations. This approach additionally facilitates the comprehensive observation of failure patterns, rates of maintenance, and operational efficacy, thereby presenting a comprehensive methodology for the management of crucial equipment.

3) The third layer: The cloud computing layer plays a crucial role in our Internet of Things (IoT) predictive maintenance architecture by serving as the fundamental infrastructure for centralized data storage, processing, and analytics. Per our objective of attaining thorough centralization, this particular layer assumes a crucial function in the consolidation and administration of the extensive volume of data produced by the predictive maintenance system for CARESCAPE R860 ICU ventilators.

The cloud infrastructure is designed to efficiently handle real-time data streams originating from a multitude of ventilators distributed across diverse healthcare institutions. The primary objective of this infrastructure is to ensure a seamless and uninterrupted flow of data, encompassing reception, storage, and processing operations. By capitalizing on the built-in scalability and flexibility offered by cloud computing, our proposed architecture guarantees the adaptability of the system to accommodate diverse data volumes and computational demands. The necessity of scalability in healthcare environments is of utmost importance, as it addresses the inherent dynamism of such settings by effectively accommodating variations in patient load and ventilator usage.

The cloud-based analytics module within our architectural framework incorporates cutting-edge algorithms and machine learning models to conduct a comprehensive analysis of the gathered data. It aims to investigate the identification of patterns, anomalies, and potential failure indicators within the specific setting at hand.

Furthermore, the presence of the cloud layer enables the convenient and efficient retrieval of essential maintenance insights from remote locations. In this study, we investigate the ability of authorized personnel, regardless of their geographical location, to securely access real-time analytics, performance trends, and predictive alerts.

In the context of security, our cloud-based architecture implements an extensive range of measures that strengthen the safety of patient data and guarantee adherence to healthcare regulations. The implementation of encryption protocols, access controls, and secure communication channels is crucial in safeguarding sensitive information that is transmitted and stored within cloud environments. These measures are designed to mitigate potential risks and threats to the confidentiality, integrity, and availability of data. By employing robust encryption protocols, data is transformed into an unreadable format, thereby preventing unauthorized access and ensuring that only authorized individuals can decipher the information.

The present study aims to investigate the utilization of cloud computing capabilities in the architecture for predictive maintenance of CARESCAPE R860 ICU ventilators. By leveraging these capabilities, the proposed architecture not only facilitates the centralization of data processing and analysis but also establishes a platform that is scalable, secure, and accessible.

4) The fourth layer: The fourth layer is the output or interface for technicians. The system indicates when humidity levels approach a dangerous threshold and alerts the technician to perform preventative maintenance before machine failure. Initially, we will implement supervised machine learning; the technician will report malfunctions to better train the algorithm through reactive decision-making. Then, proceed to semi-supervised machine learning, followed by unsupervised machine learning. The effectiveness of these methods for fault classification, anomaly detection, and real-time prediction will then be evaluated.

a) The getaway: By utilizing the ESP32 microcontroller as the gateway, we can effectively bridge the CoAP communication between the DHT22 sensor and the cloud server for predictive maintenance of the CARESCAPE R860 ventilator. Its built-in Wi-Fi, processing power, MicroPython support, community backing, and cost-effectiveness make it an excellent choice for this IoT application. The ESP32 ensures smooth data transmission, preprocessing, and security features, providing a reliable and efficient gateway solution for your predictive maintenance architecture.

b) Communication: CoAP's lightweight design and RESTful architecture make it an optimal choice for resource-constrained IoT environments, such as healthcare. By seamlessly enabling communication between the DHT22 sensor and the cloud server, CoAP efficiently transmits crucial environmental data, including temperature and humidity, in real time. This real-time data monitoring empowers prompt detection of anomalies and proactive measures for predictive maintenance. The simplicity and elegance of CoAP facilitate straightforward implementation, while its broad community support offers a rich array of libraries, tutorials, and resources, easing development efforts. CoAP is an indispensable tool in this context, showcasing its efficacy in bridging the gap between resource-constrained sensors and cloud-based infrastructure, elevating predictive maintenance capabilities, and enhancing patient safety in healthcare settings. To facilitate accurate and reliable data acquisition from the DHT22 sensor, we meticulously implemented a data retrieval method utilizing the MicroPython environment on the ESP32 microcontroller. A critical step in this process involved the installation of the ”Adafruit DHT” library, a reputable external library developed by Adafruit Industries. Leveraging the advanced features and robust error-handling mechanisms inherent to the ”Adafruit DHT” library, we ensured a seamless data acquisition process from the DHT22 sensor. Installing the ”Adafruit DHT” library involved utilizing the ”ampy” tool, a commonly used utility in the MicroPython ecosystem. This tool enabled us to efficiently copy the ”Adafruit_dht” library to the ESP32 board, allowing it to interact with the DHT22 sensor effectively.

The library installation process was methodically executed by adhering to proper software engineering practices and following established protocols. Subsequently, we crafted a specialized data retrieval function within our MicroPython script. This function, designed to interact with the DHT22 sensor, effectively accurately retrieved temperature and humidity data. Utilizing the GPIO pins and communication interfaces of the ESP32, the data retrieval function measured environmental parameters from the DHT22 sensor. The successful execution of the data retrieval method on the ESP32 microcontroller facilitated the collection of vital environmental data from the DHT22 sensor. The retrieved temperature and humidity data were foundational inputs for our predictive maintenance model, enhancing the CARESCAPE R860 ventilator's operational efficiency and patient safety. The data transfer process from the microcontroller to the cloud through CoAP in our IoT-based predictive maintenance architecture involves a systematic and efficient approach. Following the successful retrieval of environmental data from the DHT22 sensor, the ESP32 microcontroller, armed with the ”Adafruit DHT” library, acts as the intermediary gateway to facilitate seamless communication between the sensor and the cloud infrastructure. Upon data retrieval, the ESP32 microcontroller employs the CoAP protocol to package the acquired temperature and humidity data into CoAP messages, adhering to the lightweight and RESTful principles of CoAP. With the help of the built-in Wi-Fi capabilities, the ESP32 initiates a secure communication link to the cloud server, where the CoAP messages are transmitted. The CoAP server on the cloud, configured to host specific resources corresponding to the sensor data types, promptly receives the incoming CoAP messages. Using CoAP's resource observation feature, the cloud server continuously monitors the environmental data in real-time, facilitating immediate responsiveness to fluctuations in temperature and humidity levels. CoAP's Datagram Transport Layer Security (DTLS) extension is employed to ensure data integrity and privacy during transmission, safeguarding sensitive operational data from potential threats. The implementation of CoAP over DTLS provides robust security critical to the protection of patient information and the preservation of data integrity. Once the CoAP messages reach the cloud server, the data is processed, analyzed, and stored for further predictive maintenance operations. Cloud-based algorithms and analytics are employed to detect anomalies, predict potential equipment issues, and facilitate proactive maintenance actions, thus enhancing the CARESCAPE R860 ventilator's operational efficiency and reducing the risk of unplanned breakdowns. The system will continuously adjust a threshold based on the detected humidity levels that led to the failure of the ICU ventilators (Fig. 7).

The Predictive Maintenance Process for the CARESCAPE R860 involves a dynamic system that modifies a threshold based on observed humidity levels, as shown in Fig. 8. This adaptive technique is based on observations where high humidity levels were a key factor in the malfunction of ICU ventilators. The predictive maintenance technology enhances the reliability and performance of the CARESCAPE R860 ventilators by continuously monitoring and adjusting settings to proactively address possible faults.

F. Practical Deployment: Node-RED within the Proposed Architecture Framework

In this simulation (Fig. 9), we simulate the transmission of environmental data from a simulated DHT22 sensor to the cloud for processing and visualization via a secure communication method. It is important to highlight that this simulation is intended to act as a conceptual visualization to aid in understanding the proposed architecture. There is currently no active data flow; instead, it represents the projected data travel.

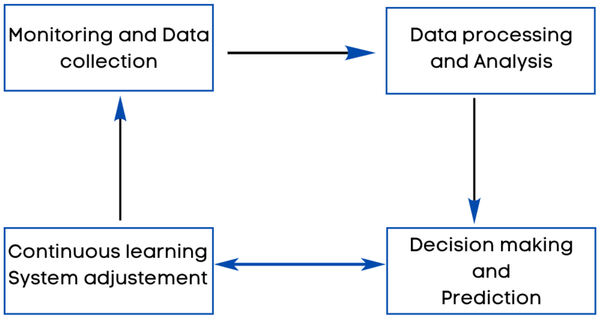
Monitoring and Data collection
Data processing and Analysis
Decision making and Prediction
Continuous learning System adjustement

Fig. 8. Predictive maintenance process for the CARESCAPE R860.

A simulated DHT22 sensor injects data, a security function applies protection measures, CoAP communication from the ESP32 microcontroller, and fog processing layer operations are all part of the sequence. Following that, the encrypted data is processed in the cloud, where it is subjected to further processing before being stored. A Debug node is strategically situated to monitor in real-time, whereas a Dashboard node is the endpoint for seeing processed data.

It is critical to note that, while this simulation assists in the conceptualization of the architecture, the real data flow implementation is part of our planned future projects.

V. Discussion

When developing our predictive maintenance architecture, we chose this specific framework based on important factors. The focus was on centralization, aiming to create a cohesive system to effectively handle predictive maintenance operations for various ventilators, with a specific emphasis on the CARESCAPE R860 model. Thorough research was conducted on the details of this particular model in a hospital unit, with a focus on key parameters that are prone to failure. This thorough approach guided the architectural design to create a customized solution for the issues related to ICU ventilators. To overcome current constraints, our design incorporates a humidity monitoring system into the chain level of the medical air filtration process. This new feature improves the capability to identify and address potential problems associated with humidity, a crucial factor highlighted in past cases of ICU ventilator malfunctions. Utilizing IoT-based predictive maintenance allows us to gather real-time data from various CARESCAPE R860 ventilators, providing a comprehensive and flexible method for monitoring equipment.

The suggested design for predictive maintenance of CARESCAPE R860 ICU ventilators is notable in the field of related studies for its thorough and inventive approach that combines IoT, fog computing, and cloud computing technologies. Standing out in the realm of predictive maintenance in healthcare, this architecture boasts a well-defined four-layer structure that covers centralized management, humidity monitoring, and real-time analytics. It is worth mentioning that the integration of adaptive threshold techniques for proactive maintenance, focus on local processing via the fog computing layer, and the use of machine learning models all play a role in its distinctiveness. This study presents a more comprehensive and innovative approach to enhancing the safety, reliability, and performance of critical medical equipment in healthcare settings, building upon previous research.

VI. Advantages and Challenges

The proposed IoT architecture represents a significant advancement in healthcare, employing predictive analytics to improve the management of mechanical ventilators. Utilizing extensive data analysis, the proposed framework holds the potential to enhance the quality and effectiveness of healthcare services by addressing the challenges posed by equipment malfunctions. This is vital for ensuring the well-being of patients and optimizing organizational expenses.

This architecture uses a centralized data approach to consolidate information from multiple CARESCAPE R860 ventilators, allowing for unified analysis and proactive maintenance strategies. The incorporation of IoT technology guarantees the ability to monitor in real time, facilitates effective communication, and enhances the dependability of the system. Intuitive interfaces and comprehensive training enable healthcare professionals to effectively analyze machine learning insights, enhancing the efficiency of the predictive maintenance model.

The architecture offers a versatile solution that can be applied to various hospital settings, showcasing its strengths in scalability and adaptability. This novel approach effectively streamlines predictive maintenance, optimizes workflows, and enhances patient safety, thereby contributing to the advancement of healthcare services.

However, due to their complex infrastructures and programming models, emerging data technologies necessitate a high level of data science and IT domain expertise in order to be utilized and installed. This is the main challenge of the proposed framework. This may impede the adoption of big data technologies in the healthcare industry.

The successful deployment of a system of this nature necessitates addressing not only the technical challenges but also the ethical implications that arise. The issues regarding the preservation of patient confidentiality, acquisition of informed consent, and the conscientious utilization of health-related information. The delicate balance between maximizing the advantages of predictive analytics and safeguarding the confidentiality of sensitive patient data necessitates diligent contemplation and adherence to ethical principles.

The issue of security presents itself as a significant challenge within the context of implementing the suggested architectural framework. The system deals with the management of sensitive health data, emphasizing the necessity of implementing robust security measures to effectively protect against unauthorized access, data breaches, and potential misuse. The preservation of patient data integrity and confidentiality is of utmost importance to achieve optimal performance and widespread adoption of the predictive maintenance system [9].

The utilization of embedded systems presents a set of obstacles, particularly within the realm of healthcare envi-

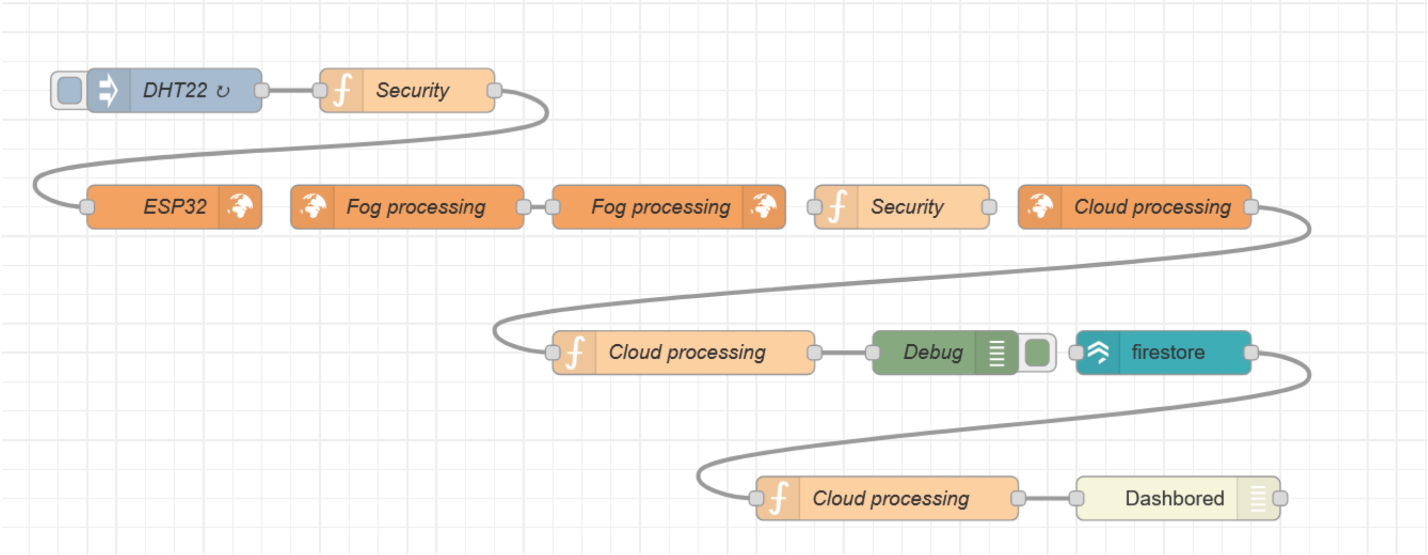

Fig. 9. Visual diagram of Node-RED implementation.

ronments, wherein the crucial role of reliability and real-time responsiveness is evident. The successful integration and ongoing maintenance of embedded systems in the context of ventilators necessitates a meticulous and methodical approach to guarantee seamless functionality and reduce any potential disruptions to healthcare services.

The human factor is a challenging aspect that requires careful analysis and attention when implementing predictive maintenance systems. In healthcare, healthcare professionals and staff must acquire the necessary knowledge and skills to effectively use and understand the data generated by the predictive maintenance system. This is essential for ensuring high-stakes patient care.

One notable facet of this challenge is the necessity for healthcare personnel to have knowledge and skills in machine learning for this to succeed [8]. Healthcare professionals need to have a thorough understanding of the machine learning algorithms used in the predictive maintenance system to accurately interpret the predictions and recommendations provided by the model. This knowledge enables them to differentiate between typical system functioning and possible irregularities, facilitating prompt and well-informed decision-making.

Moreover, Healthcare personnel need a thorough understanding of how the predictive maintenance system works. Understanding a system requires knowledge of both its technical components and its operational intricacies. Training programs should provide healthcare professionals with a comprehensive understanding of the functioning of the system, including its data inputs and the underlying logic used for making predictions.

In addition to their expertise in machine learning, healthcare personnel need to have a comprehensive understanding of the healthcare system and how it integrates with existing hospital workflows. This comprehension guarantees a seamless cooperation between predictive maintenance technology and the everyday functions of healthcare environments. It facilitates the integration of system insights into healthcare professionals' decision-making.

It is important to consider the concerns and preferences of healthcare workers. Effective communication, thorough training, and continuous support are crucial for establishing confidence and trust in predictive maintenance technology. Healthcare professionals should be knowledgeable and confident in using technology to improve patient care and make maintenance processes more efficient.

The complex nature of introducing AI and IoT technologies in healthcare is underscored by a range of challenges, including technical complexity, ethical considerations, security, embedded systems integration, and the human factor. The successful resolution of these obstacles is of utmost importance to fully unlock the capabilities of predictive maintenance systems and guarantee their beneficial effects on patient care and operational efficacy.

VII. Conclusion

This article presented a real-time monitoring architecture for inspecting and maintaining ICU ventilators in several healthcare organizations. Since the quality and quantities of medical devices in hospitals have increased, traditional maintenance techniques could have been more efficient and practical. The proposed architecture enables biomedical engineers or technicians to monitor the outcomes of data analysis, the predicted health status of ICU ventilators, and maintenance schedules in real time through device notifications and live charts. Consequently, the occurrence of a significant event on the selected devices can be detected and communicated to interested parties in real time. This architecture uses big data and IoT technologies to identify any component wear or breakage and monitor the status of these ventilators. It is founded on the monitoring and surveillance of the pneumatic block. Implementing an intelligent humidity detection system is optimal, as humidity monitoring significantly contributes to product quality. Sufficiently dry and only compressed air can reduce the risk of corrosion and condensation, equipment failures, and poor product quality.

As for our future projects, we aim to achieve a system-wide predictive maintenance system by implementing an integrity monitoring framework.

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Predicting Aircraft Engine Failures using Artificial Intelligence

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***Abstract*—Nowadays, the aviation sector continues to develop especially with the emergence of new technologies, and solutions. Hence, there is an increasing demand for enhanced safety and operational efficiency in the aviation industry. As to guarantee this safety, the aircraft's engines must be monitored, controlled and maintained, however in an efficient way. Thus, the research community is working continuously in order to provide solutions that are efficient and cost effective. Artificial intelligence and more specifically machine learning models have been employed in this sense. Here comes the proposition of this article. It presents solutions implementing predictive maintenance using machine learning models. They help in predicting aircraft's failures. This is in order to avoid operations of unscheduled maintenance and disruptions of services.**

Keywords*—*Aircraft engine failures; machine learning; predictive maintenance; C-MAPSS; aviation safety

I. Introduction

The aviation industry has entered a new phase of aircraft maintenance and reliability through the integration of cutting-edge technology and advanced data analysis. In aviation, the availability and well functioning of aircraft components have always been crucial. Aircraft systems and component availability is increased by making accurate failure predictions. The timing of maintenance operations is a crucial factor in determining the total cost of maintenance and overhaul for aircraft components, which account for a substantial amount of all operating expenses for aviation systems. In the aviation industry, there are three primary forms of equipment maintenance. Corrective maintenance deals with maintenance procedures and unplanned issues, such as machine and equipment breakdowns, that arise when using aircraft equipment. Preventive maintenance aims to reduce unplanned repairs through periodic maintenance, preventing equipment failures or machinery breakdowns. Tasks are planned to avoid unexpected downtime and breakdown events, minimizing the need for repair operations. Predictive maintenance, as its name implies, utilizes parameters measured during equipment operation to anticipate potential failures. Its goal is to intervene before faults occur, reducing unexpected failures by providing people working in maintenance, with more reliable scheduling options for preventive maintenance. Evaluating system reliability is crucial in selecting the appropriate maintenance strategy. With the emergence of artificial intelligence technologies, preventive maintenance has know interesting progress. Thanks to AI approaches, and its ability to analyse large historical data including aircraft components, engine performance, sensor readings, and maintenance records, preventive analytics can be implemented in order to predict issues before they happen. This reduces the risk of unplanned downtime and allow timely intervention. AI also helps in the efficient prioritisation of tasks based on their criticality, and optimises the resources allocation accordingly. Finally, AI technologies allow the monitoring of aircrafts in real time thanks to deploying sensor and other IoT devices on the aircrafts components in order to monitor their health and performance. In this article, one of the aspects of AI will be used to implement the predictive maintenance, which is the machine learning one. The choice of these models is based on their performance in the literature. They will be explored in analysing and exploring the extensive Commercial Modular Aero-Propulsion System Simulation (CMAPSS) dataset. The article suggests an approach that starts with an in depth exploration and preparation of the data which is the core module of machine learning and the decision making system. This includes using histograms to understand the distribution of relevant variables. This step offers insights into the statistical characteristics of the data and aids in identifying potential patterns and anomalies. This process involves selecting and engineering relevant attributes that provide a comprehensive view of engine health and potential failure scenarios. These meticulous steps serve as the foundation for constructing robust predictive models with the potential to redefine aviation maintenance practices, which is the next step of building machine learning models. This article elucidates the significance of these advancements, the methodologies deployed, the resulting insights, and their far-reaching implications for the aerospace industry in order to enhance the safety and efficiency of aircraft engines.

A. Problem Statement

Predictive maintenance in aviation is a key factor in ensuring flight safety and performance. Using advanced technologies such as analysis of sensor data, artificial intelligence, airlines can anticipate potential failures and take corrective action before problems become critical. This proactive approach helps minimize flight interruptions, reduce maintenance costs and optimize resources use. It is within this framework that this project is located.
Hence, here the main issue is how to allow the prediction of these engines' failures?

II. Related Works

Prognostics and health management are critical in today's industrial big data era because they improve the accuracy of failure predictions in the future, which reduces expenses associated with inventory, maintenance, and labor. The NASA Commercial Modular Aero-Propulsion System Simulation dataset, an open-source benchmark with simulated turbofan engine units subjected to realistic flight circumstances, was used for the 2021 PHM Data Challenge. The goal of earlier deep learning applications in this field was to forecast how long engine units would stay useful. Nevertheless, the lack of identification of failure mode information in these methods, has limited their Interpretability and practical usefulness.

To overcome these constraints, a novel prognostics approach has been introduced, incorporating a tailored loss function. This approach aims to concurrently assess the remaining usable life, identify the probable failing component or components, and anticipate the current state of health. The suggested approach combines principal component analysis to orthogonalize statistical time-domain characteristics, which are then fed into supervised regressors like XGBoost, artificial neural networks, random forests and extreme random forests. Almong these approaches, ANN-Flux was considered to be the most effective, with AUROC and AUPR values higher than 0.95 for every classification assignment.

Furthermore, ANN-Flux demonstrates a remarkable 38% reduction in the root mean square error (RMSE) for remaining useful life compared to previous methodologies, utilizing the same test split of the dataset. Importantly, this improvement is achieved with significantly less computational cost, showcasing the potential of the proposed approach in advancing the field of prognostics and health management in industrial contexts [1].

This study describes the aviation industry, and how it involves a vast amount of information and maintenance data holding the potential to yield meaningful insights into forecasting future actions. This study seeks to introduce machine learning models that include feature selection and data elimination techniques for predicting aircraft systems failures. Over a two-year period, maintenance and failure data for aircraft equipments were systematically collected, identifying nine input variables and one output variable. A hybrid data preparation model is proposed to enhance the accuracy of failure count predictions in a two-stage process.

The first step uses ReliefF, a feature selection technique, to determine which factors have the greatest and least impact. To remove inconsistent or noisy data, a modified version of the K-means method is applied in the next step. Using Multilayer Perceptron (MLP) as an Artificial Neural Network (ANN), Support Vector Regression (SVR), and Linear Regression (LR) as machine learning techniques, the hybrid data preparation model's performance is evaluated on the maintenance dataset. The models' efficacy is measured using evaluation measures such as the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Correlation Coefficient (CC).

The findings indicate that the hybrid data preparation model successfully predicts the failure count of the equipment, showcasing its efficiency in enhancing the accuracy of forecasting in the aviation industry [2].

An essential facilitator of intelligent maintenance systems is the capability to foresee the remaining useful lifetime (RUL) of their components, known as prognostics. Constructing data-driven prognostics models necessitates datasets that encompass run-to-failure trajectories. Nevertheless, in many real-world applications, obtaining large, representative run-to-failure datasets proves challenging as failures are infrequent in numerous safety-critical systems. In order to stimulate the advancement of prognostics methodologies, authors in [3] have formulated a new authentic dataset comprising run-to-failure trajectories for a fleet of aircraft engines operating under genuine flight conditions. This dataset was generated utilizing the Commercial Modular AeroPropulsion System Simulation (CMAPSS) model developed by NASA.

This dataset incorporates damage propagation modeling that adds two more levels of accuracy to the methodology developed in previous research. First of all, it takes into consideration actual flying circumstances as reported by a commercial aircraft. By connecting the degradation process to its operational history, it also improves the degradation modeling. This dataset is useful not just for predictive issues but also for providing health and fault class information. Because of this, it has two uses: it can be used for fault diagnostics as well as prognostics.

It is necessary to have datasets with run-to-failure trajectories available in order to generate data-driven prognostic models. The dataset offers a new realistic dataset of run-to-failure trajectories for a small fleet of aircraft engines under realistic flight conditions in order to aid in the development of these approaches. This synthetic dataset was created using damage propagation modeling, which adds two new levels of authenticity to the modeling approach utilized in earlier research. It starts by taking into account actual flight circumstances as reported by a commercial aircraft. By connecting the degradation process to the operating history, it further expands the degradation modeling. The dataset was created using the dynamic model of the Commercial Modular AeroPropulsion System Simulation (C-MAPSS) [4].

This study [5] outlines the methodology for modeling damage propagation within the components of aircraft gas turbine engines. The proposed approach involves generating response surfaces for all sensors through a thermo-dynamical simulation model that considers variations in flow and efficiency across the modules of interest. Specifically, an exponential rate of change for both flow and efficiency loss is applied to each dataset, starting from a randomly selected initial deterioration set point. The rate of change signifies an unspecified fault with a progressively deteriorating impact, with constraints on the upper threshold but otherwise random selection for fault rates.

Damage can continue to spread until a certain failure criterion is satisfied. At each instant in time, a health index is defined as the minimum of several overlaying operating margins; when the health index approaches zero, the failure criterion is met. The time series (cycles) of sensed measurements, usually from aircraft gas turbine engines, make up the model's output. The produced data are used by Prognostics and Health Management (PHM) as challenge data [6].

III. The Proposed Approach

The main objective of this work is to set up a system capable of predicting potential failures in the turbofan engine of aircraft. To do this, an accurate and reliable artificial intelligence model was created, using data analysis and predictive techniques to anticipate failures.

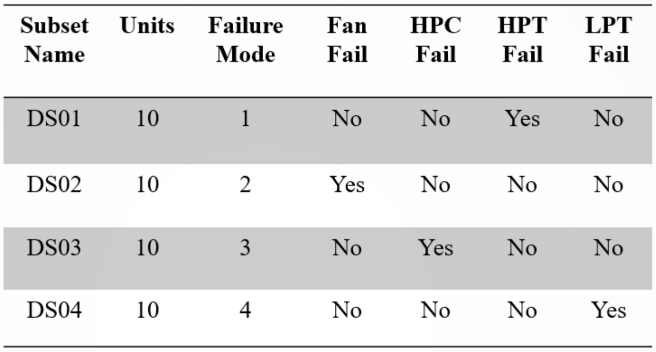
- Early detection of anomalies: The main objective is to use models and advanced AI technologies to detect early signs of anomalies or failures in the engine before they become critical.

- Increasing aircraft reliability: By identifying potential failures in advance, this work aims to improving the flight reliability and safety.

Initially, a detailed description of the C-MAPSS dataset is provided, including an introduction to the input variables and dataset composition. The suggested approach uses the categorization method in order to predict the eventual failure components. Three steps sum up the proposed methodology: First, histograms 2) Equilibrium data 3) smoothing of data 4) extraction of features; 5) obtaining the final predictions by developing a supervised machine learning model.

A. Dataset Description

The N-CMAPSS dataset has 40 engine units altogether and is divided into four supplied subsets. An overview of the failure mechanisms found in each subset is given in Fig. 1. The dataset's overall goal is to predict the RUL till catastrophic failure. Engine units are normally rated between 60 and 100 cycles. The duration of each flight cycle varies, and it is distinguished by 18 time series signals: Four descriptors of the flight data that summarize the dynamic operating conditions and fourteen real-time sensor measurements. Each cycle comprises the following additional variables in addition to the time series signals that are helpful in understanding the context of a flight cycle: the unit number, cycle number, a binary health state variable hs (set to 0 for unhealthy status and 1 for healthy status), and a categorical flight class variable Fc that represents the flight' length that is (set to 1 for short flights, 2 for medium flights, and 3 for long flights). Here, the simulated engines are operated past their optimal state until they eventually shut down [7].



Subset Name	Units	Failure Mode	Fan Fail	HPC Fail	HPT Fail	LPT Fail
DS01	10	1	No	No	Yes	No
DS02	10	2	Yes	No	No	No
DS03	10	3	No	Yes	No	No
DS04	10	4	No	No	No	Yes

Fig. 1. The N-CMAPSS dataset failure mode description.

B. Data Preparation

1) *Histograms:* To analyze the distribution of values in the dataset, a histogram was created, as shown in the Fig. 2 below. This histogram provides a clear graphical representation of the frequencies of the different values of the variable to be studied. On the horizontal axis, the different ranges of values were placed, and on the vertical axis, the frequency or density of occurrences in each bin, was represented. The shape of the histogram gives us immediate insight into the central tendency, the overall shape of the data distribution. This visualization allows us to identify patterns, thus providing important information for understanding the nature of this dataset.

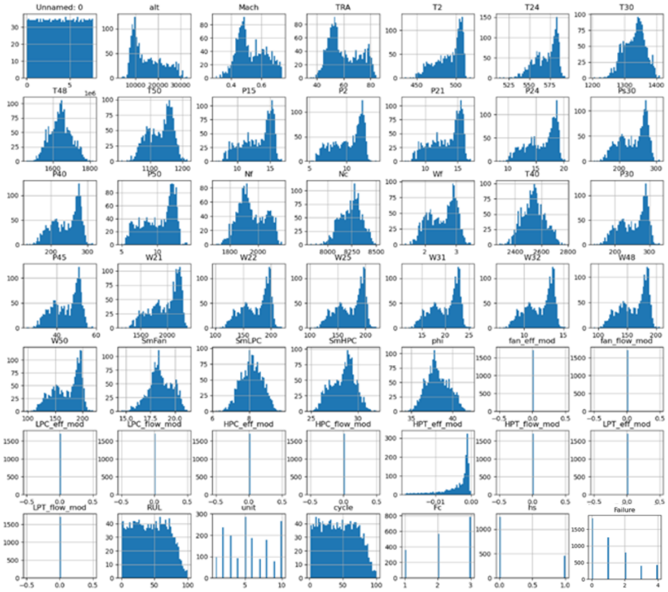


Fig. 2. The distribution of the N-CMAPSS dataset.

2) *Data balancing:* To address the issue of unbalanced data which is a challenging issue in machine learning, the Synthetic Minority Over-sampling Technique (SMOTE) has been opted in that sense. When one class significantly outnumbers the other, it can lead to biased model performance. SMOTE offers a solution by creating synthetic instances of the minority class. By interpolating between existing data points, SMOTE effectively increases the number of minority class samples, rebalancing the dataset. This approach not only mitigates the bias but also enables machine learning models to better recognize and generalize from the minority class. When coupled with other techniques or algorithms, SMOTE contributes to improved classification accuracy and, in turn, more robust and equitable model predictions [8] (Fig. 3 and 4).

3) *Data smoothing:* Using the Simple Moving Average (SMA), which is a straightforward yet effective technique widely employed in data analysis and time series forecasting. as shown in Fig. 5, SMA involves calculating the average of a fixed number of data points within a specified window or interval. This rolling average smooths out short-term fluctuations and emphasizes the overall trend in the data. SMA is particularly useful in identifying trends, cycles, and underlying patterns in time series data. Its simplicity and ease of implementation make it a popular choice for quick, preliminary analyses and trend detection. By reducing noise and highlighting long-term changes, SMA offers valuable insights for decision-making across various domains [9] (Fig. 5).

4) *Data normalization:* The Min-Max Scaler was used which is a widely used technique in data preprocessing, particularly in machine learning and statistics. This method

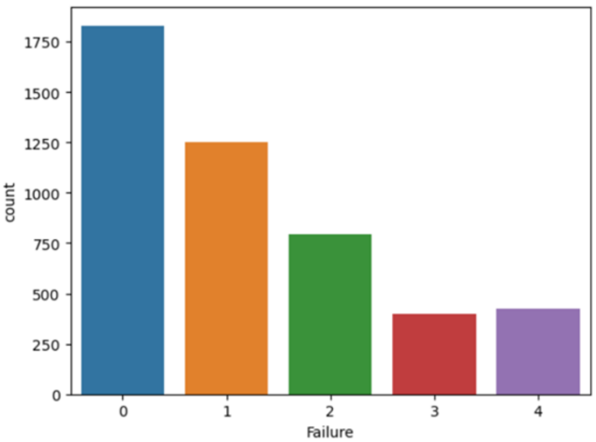


Fig. 3. The imbalanced dataset classes.

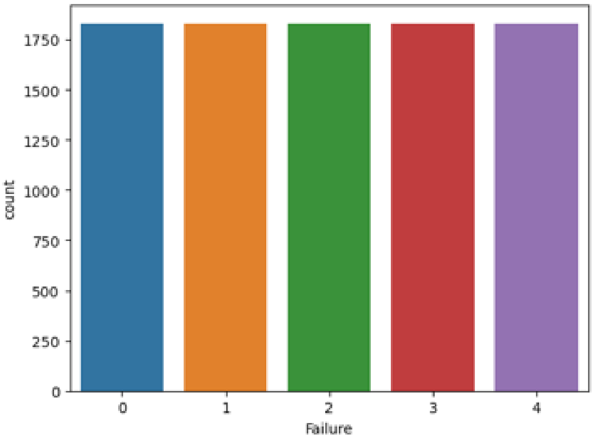


Fig. 4. The balanced dataset classes after using smote method.

scales and transforms data to fit within a specified range, typically between 0 and 1, by subtracting the minimum value and dividing by the range of values within a feature. The Min-Max Scaler ensures that all features share a common scale, eliminating discrepancies in magnitudes and helping machine learning models perform optimally. This approach is valuable in scenarios where maintaining the original data distribution is not critical, and consistent feature scaling is more crucial [10].

C. Feature Extraction

Feature extraction is a fundamental process in data analysis and machine learning that involves transforming raw data into a more concise and informative representation. The objective is to retain essential information while reducing dimensionality and computational complexity. In essence, feature extraction selects the most relevant attributes or characteristics from the original dataset, thereby enhancing the efficiency and effectiveness of subsequent analysis or modeling [11].

Selection and extraction of features are required in order to lower the dataset's input dimensionality. Fig. 1 of the C-MAPSS dataset shows that there are only 40 turbofan engine units; however, the dataset has over 63 million timestamps and needs to be reduced for further data processing. Predictions were provided on a per-cycle basis, as in earlier studies.

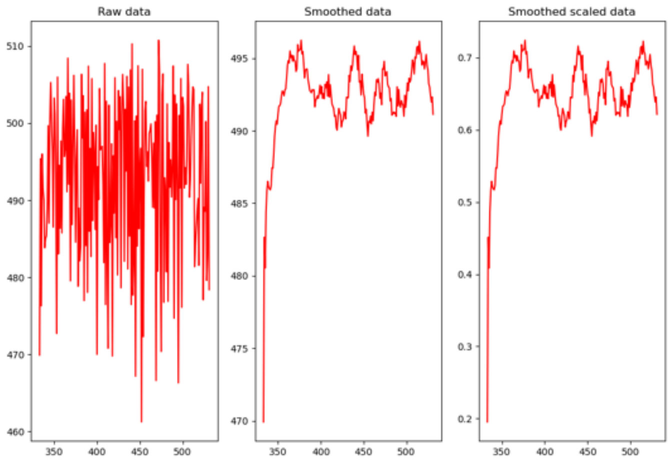


Fig. 5. The dataset before and after data smoothing.

$$\text{Scaled Value } (x') = \frac{x - \text{min}}{\text{max} - \text{min}}$$

In this article, the main focus is on the extraction of the cycle-wide statistical time domain feature to summarize the distribution for each time series using the mean.

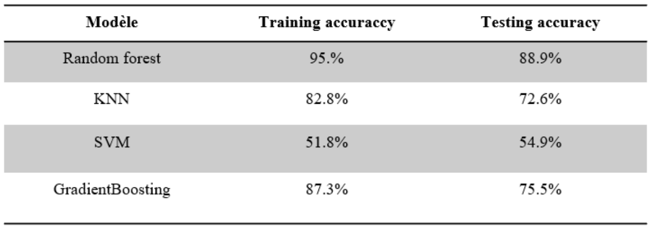
D. Training the Models

In this article, four diverse machine learning models have been trained and developped including: Random forest [12], Support Vector Machines (SVM) [13], K-Nearest Neighbors (KNN) [14], and Gradient Boosting [15]. Each of these models represents a unique approach to solving predictive tasks, showcasing the versatility of machine learning techniques.

Here are the reasons why these models have been chosen. Decision Trees are known for their simplicity and interpretability. They are like a flowchart, making decisions by splitting data based on features. SVM, on the other hand, excels at finding optimal decision boundaries, making it valuable in tasks like classification and regression. K-Nearest Neighbors relies on the wisdom of the crowd, assigning data points to the most common class among their neighbors, while Gradient Boosting combines the wisdom of many weak learners to create a robust, ensemble model (Fig. 6).

E. Hyperparameters Finetuning

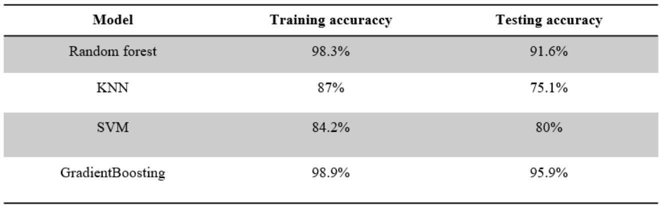
Hyperparameter adjustment is a pivotal phase in fine-tuning machine learning models, where the optimal set of hyperparameters is sought to achieve peak model performance. These hyperparameters, like learning rates, regularization terms, or tree depths, shape a model's behavior and its ability to generalize to new data. Two prominent methods for hyperparameter optimization are Grid Search and Random Search [16]



Modèle	Training accuraccy	Testing accuracy
Random forest	95.%	88.9%
KNN	82.8%	72.6%
SVM	51.8%	54.9%
GradientBoosting	87.3%	75.5%

Fig. 6. Models accuracy with the defaults parameters.

Grid Search systematically explores a predefined hyperparameters space by evaluating models at various combinations of hyperparameters' values. It involves a structured and exhaustive search, where every possible combination is assessed. While Grid Search ensures thorough coverage of the hyperparameters space, it can be computationally expensive and impractical for large search spaces [17] (Fig. 7).

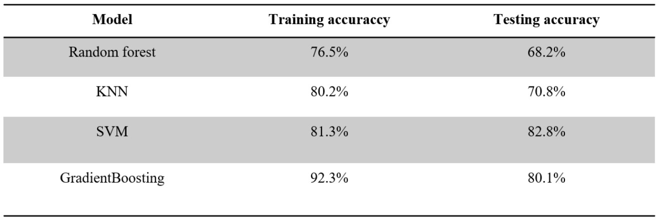


Model	Training accuraccy	Testing accuracy
Random forest	98.3%	91.6%
KNN	87%	75.1%
SVM	84.2%	80%
GradientBoosting	98.9%	95.9%

Fig. 7. Models accuracy with the Grid Search parameters.

In contrast, Random Search takes a more stochastic approach. It randomly samples hyperparameters values from specified distributions, which allows for a more efficient exploration of the hyperparameters space. Random Search can often yield excellent results with fewer iterations, making it a valuable alternative, particularly in scenarios where computational resources are limited [18].

Both methods serve as powerful tools for finding the optimal hyperparameters. The choice between Grid Search and Random Search depends on the nature of the problem, available resources, and the desired balance between thoroughness and efficiency in the hyperparameter optimization process (Fig. 8).



Model	Training accuraccy	Testing accuracy
Random forest	76.5%	68.2%
KNN	80.2%	70.8%
SVM	81.3%	82.8%
GradientBoosting	92.3%	80.1%

Fig. 8. Models accuracy with the Random Search parameters.

IV. Results

The comparative analysis of machine learning models' performances on the engines' related data within was conducted with particular rigor to select the model best suited to the studied problem. The four examined models, namely Random Forest, kNN, SVM, and Gradient Boosting, underwent thorough evaluation, with meticulous optimization of their hyperparameters to maximize their performance.

The results of this evaluation revealed interesting achievements. As shown in the figure, the Gradient Boosting model emerged as the leader, displaying a remarkable accuracy of 90.9%. This outstanding result underscores the model's ability to effectively capture complex and non-linear relationships present in the dataset. The superior performance of Gradient Boosting compared to other models indicates its relevance and predictive power for the specific application.

The decision to select the Gradient Boosting model as the final model is supported by this superior performance. However, it is crucial to consider other aspects, such as the model's complexity and the resources required for its deployment. While Gradient Boosting is powerful, it may be more demanding in terms of training time and computational resources (Fig. 9).

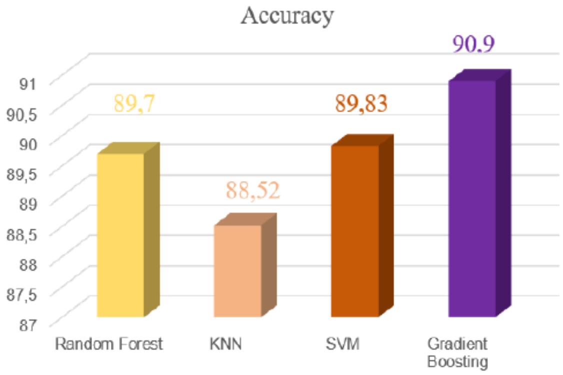


Fig. 9. The performance of the models.

As to position our results, gradient boosting algorithm in this article has given better accuracy value thanks to the used finetuning methods. If compared with the literature results [19], it gave better results. For example, in this article, gradient boosting has given less interesting results when applied to aircraft' dataset.

V. Conclusion

In conclusion, this article has performed a fascinating exploration of the world of machine learning in the context of predicting aircraft engine failures. A deep dive has been taken into the intricacies of four key machine learning models: Gradient Boosting, Decision Trees, Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). These models serve as powerful tools in addressing the critical challenge of aviation engine reliability.

Throughout this journey, the inner workings of these models has been identified and their implication in the real-world applications in enhancing aircraft maintenance practices, has been witnessed. The significance of predictive maintenance in aviation safety and efficiency cannot be overstated, and machine learning provides a pathway to achieving this pivotal goal. Furthermore, the article has shed light on the importance of hyperparameters' adjustment, as well as two powerful techniques, Grid Search and Random Search, that empower data scientists to fine-tune these models. This hyperparameters' optimization process represents a crucial step in ensuring the effectiveness of AI-driven predictive maintenance. In the realm of aviation, where safety is paramount, the fusion of data and artificial intelligence is transforming the landscape of engine failure prediction. The diversity of machine learning models, coupled with meticulous hyperparameters' tuning, have allowed the proactive detection and handling of potential engine issues, thus enhancing both the safety and efficiency of aircraft operations. Thus, the domain of Artificial intelligence is going to play a pivotal role in redefining the standards of excellence in aircraft engine maintenance.

VI. Data Availability

Concerning the availability of the C-MAPSS dataset, it can be downloaded from the Center of Excellence Data Repository of NASA; through the following link: https://www.nasa.gov/content/prognostics-center-of-excellence-data-set-repository.

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A Hybrid Model for Ischemic Stroke Brain Segmentation from MRI Images using CBAM and ResNet50-UNet

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***Abstract*—Ischemic stroke is the most prevalent type of stroke and a leading cause of mortality and long-term impairment globally. Timely identification, precise localization, and early detection of ischemic stroke lesions brain are critical in healthcare. Various modalities are employed for detection, and magnetic resonance imaging stands out as the most effective. Different magnetic resonance imaging techniques have been proposed for the detection of ischemic stroke lesion tumors, allowing for image uploading and visualization. Automated segmentation of ischemic stroke lesions from magnetic resonance imaging images has an important role in the analysis, prognostic, diagnosis, and clinical treatment planning of some neurological diseases. Recently, computer-aided diagnosis systems based on deep learning techniques have demonstrated significant promise in medical image analysis, particularly in multi-modality medical image segmentation. Automated segmentation is a difficult task due to the enormous quantity of data provided by magnetic resonance imaging and the variation in the location and size of the lesion. In this study, we develop an automated computer-aided diagnosis system for the automatic segmentation of ischemic stroke lesions from magnetic resonance imaging images using a Convolution Block Attention Module (CBAM) and hybrid UNet-ResNet50 model. The UNet model is integrated into the architecture, and the ResNet50 backbone is pre-trained to enhance feature extraction. CBAM block is a model applied in this approach to extract the most effective feature maps. The proposed approach is evaluated on the public Ischemic Stroke Lesion Segmentation Challenge 2015 dataset, arranged into weighted-T1(T1), weighted-T2(T2), FLAIR, and DWI sequences. Experimental results demonstrate the efficacy of our approach, achieving an impressive accuracy value of 99.56%, a precision value of 97.12%, and a DC of 79.6%. Notably, our approach outperforms other state-of-the-art methods, particularly in terms of accuracy values, highlighting its potential as a robust tool for automated ischemic stroke lesion segmentation in magnetic resonance imaging.**

Keywords*—*Medical image segmentation; ischemic stroke disease; UNet; ResNet50; convolution block attention module; magnetic resonance imaging; transfer learning

I. Introduction

Stroke, characterized by the sudden onset of cerebral dysfunction, is a global health concern with significant mortality rates and long-term disability [1]. Recognized as a pandemic by the World Health Organization (WHO), the projected increase in stroke cases underscores its growing impact, with estimates reaching 23 million by 2030 [2], [3], [4]. This surge in incidence, now at 12 million cases annually, demands heightened attention from the medical community [5].

In the United States, approximately 800,000 people suffer from strokes each year, a number expected to significantly increase in the future due to the aging population [6]. In Tunisia, stroke stands as the leading cause of physical disability in adults and the third cause of death, with an annual incidence of around 10,000 new cases [7]. The aftermath of stroke, affecting around 70% of survivors, are often left with severe cognitive problems, requiring intensive and specialized care over a long period to facilitate recovery [3].

Stroke is categorized into two primary types: ischemic and hemorrhagic. In this study, we focuses on Ischemic Stroke Lesions (ISL) due to their widespread prevalence and the imperative for early intervention, including thrombolysis or thrombectomy. The automatic segmentation of ischemic stroke lesions from Magnetic Resonance Imaging (MRI) images plays a pivotal role in improving diagnosis, prediction, and treatment planning. Advanced neuroimaging modalities, particularly MRI, have proven indispensable in enhancing the efficiency and accuracy of stroke interventions.

In our research, we focused on Ischemic Stroke Lesions (ISL) because they affect a lot of people and require early intervention and treatment which will be acts of thrombolysis or thrombectomy. Additionally, the assessment of ischemic stroke lesions is a critical endpoint in clinical trials. It can help to improve how we diagnose, predict, find, and treat this condition. The evaluation of ischemic stroke lesions is a pivotal endpoint in clinical trials, offering insights that can enhance diagnosis, prediction, localization, and treatment. The advancements in medical imaging technology have significantly improved the intervention and clinical treatment of strokes, making them more efficient and accurate. Advanced neuroimaging modalities including Magnetic Resonance Imaging (MRI), Computed Tomography(CT scan), and Magnetic Resonance Angiography (MRA), etc, are used for ISL diagnosis. CT imaging can diagnose stroke patients who have tumors well, but it is not good at showing other parts of the brain or early signs of damage. Angiography means putting an injection of a contrast agent into the patient, which can affect their health and cause implications for the patient's body [8]. MRI emerges as the most effective tool for assessing patients with ischemic stroke. It is a non-invasive tool, more sensitive and it can accurately analyze the diseases. It can help to track the disease and predict the outcome. Furthermore, her sequence acquisitions (Diffusion-Weighted-Images (DWI), T1, T2, and Fluid-Attenuated-Inversion-Recovery (FLAIR)), can provide specific information about the extent of the lesion and her localization which represents the main clinical detail in detection processing. Its multi-parametric nature, encompassing various contrasts and sequences, positions MRI as an indispensable and highly effective method for the comprehensive assessment of ischemic stroke patients, thereby influencing critical aspects of their care and recovery. The ability to automatically detect infarct lesions proves invaluable for medical diagnosis, facilitating timely intervention and treatment planning. MRI stands as a cornerstone in post-stroke issue resolution, offering unparalleled advantages such as detailed disease monitoring, early lesion visualization, tissue characterization, and outcome prediction.

Ischemic strokes have a complex structure that makes their segmentation in MRI images difficult. Therefore, automatic stroke segmentation has been achieved by using Artificial Intelligence (AI) algorithms, which are very important for the medical research field. AI techniques, such as deep learning and machine learning, are very popular in the medical field. They can handle multidimensional medical data as well as a trained expert. Moreover, it is widely used and adopted in the process of medical imaging processing, especially in segmentation, classification, diagnosis, detection, and prognosis of stroke ischemia. It offers reliable, accurate, and consistent outcomes. This would reduce the testing time and enable the neuroradiologists to examine and interpret more data for their patients, which would be more cost-efficient.

Currently, various Computer-Aided Diagnosis (CAD) systems based on deep learning models are commonly developed and applied in ISL segmentation. Specifically, Convolutional neural networks (CNNs) are the most employed models for image classification and segmentation tasks in neurodegenerative diseases. CNN has demonstrated enormous potential in analyzing and characterizing medical images, including ischemic brain stroke segmentation. Furthermore, these models have leveraged the power of CNNs for image analysis and the advantages of statistical methods for data processing. This makes many patterns have been developed by researchers around the world.

However, CNNs often suffer from limitations when segmenting medical images, due to their limited spatial awareness and difficulty in processing diverse anatomical structures. To overcome these difficulties, the adoption of the Convolutional Block Attention Module (CBAM) is proving advantageous. CBAM remedies the rigidity of CNN by incorporating attention mechanisms that enhance spatial awareness, enabling the model to capture long-range dependencies in medical images. In addition, the dynamic importance of CBAM features facilitates adaptation to complex structures, enabling the network to focus on relevant regions and improve segmentation accuracy. This transition to CBAM represents a promising advance in medical image analysis, offering a more robust and flexible approach to image segmentation tasks.

In this paper, we propose a CAD system for ischemic stroke brain segmentation based on CBAM and a hybrid ResNet50-Unet model from MRI sequences to overcome these issues. We enhance the ResNet50-UNet architecture performance by integrating the CBAM block. The ResNet50-UNet framework combines the deep feature extraction capabilities of ResNet50 with the precise segmentation abilities of the UNet architecture. To introduce attention mechanisms and enrich feature representations, we meticulously inserted CBAM block after each convolutional block within the network. At each convolution step, the CBAM module dynamically computes channel-wise and spatial-wise attention, allowing the model to focus on relevant features and significant regions in the medical images. This customized integration gives our model greater spatial awareness and adaptability to complex anatomical structures, increasing segmentation accuracy compared to the conventional ResNet50-UNet architecture. The CBAM-enhanced ResNet50-UNet not only leverages the strength of both architectures but also capitalizes on the attention mechanisms to achieve more refined, context-sensitive segmentation of medical images.

In this study, we propose a systematic approach for the segmentation of ischemic stroke brain lesions using a Computer-Aided Diagnosis (CAD) system. Our method employs a hybrid ResNet50-Unet model, and we enhance its capabilities by integrating the Convolutional Block Attention Module (CBAM) into the processing of MRI sequences. The methodology unfolds through several key steps. We begin by integrating a CBAM block into the ResNet50-UNet architecture, a step designed to significantly improve the model's performance. This integration capitalizes on the deep feature extraction prowess of ResNet50 while harnessing the precise segmentation abilities inherent in the UNet architecture. Subsequently, attention mechanisms are introduced by strategically placing a CBAM block after each convolutional block within the network. This meticulous insertion allows for the dynamic computation of channel-wise and spatial-wise attention at every convolutional step. As a result, the model becomes adept at focusing on relevant features and significant regions in the medical images. To further refine the approach, we customize the integration, providing our model with heightened spatial awareness and adaptability to complex anatomical structures. This customization proves instrumental in increasing segmentation accuracy compared to the conventional ResNet50-UNet architecture. The culmination of these efforts results in a CBAM-enhanced ResNet50-UNet model that not only leverages the strengths of both architectures but also effectively utilizes attention mechanisms to achieve a more refined and context-sensitive segmentation of medical images. This approach holds promise for advancing the field of ischemic stroke diagnosis and treatment planning.

The remaining parts of this research paper are organized as follows: In section two, we review the current reviews state of the art techniques segmentation for ISL. In Section Three, we present the dataset description and preprocessing and, eventually, discuss the proposed method based on mechanism attention and ResNet50-UNet (CBAM ResnNet50-UNet). Section four reports the experimental results and compares our method with the results of the state-of-the-art multimodal MRI dataset Ischemic Stroke Lesion Segmentation Challenge (ISLES) 2015. We also address some important challenges and drawbacks of the methods we propose in the same section. Finally, the paper is concluded in Section Five.

II. Related Work

Machine learning (ML) and deep learning (DL) have transformed the landscape of medical imaging significantly, providing unparalleled capabilities in analyzing intricate datasets. Classical machine learning methods heavily depended on features manually designed for the analysis of brain images. Identifying abnormalities, particularly in cases such as brain ischemia, presented challenges owing to irregular shapes and ambiguous boundaries. Deep learning models, specifically CNNs, autonomously acquire both local and global features, proving crucial for early diagnosis. In the context of brain ischemia, various methods leveraging CNNs have been developed for automatic early detection and segmentation. This section provides an in-depth overview of leading methods for brain ischemia segmentation from multimodal MRI sequences. Utilizing the ISLES 2015 dataset, which aligns with my proposed approach, our analysis aims to capture insights accumulated between 2017 and May 2023.

Kamnitsas et al. [9] proposed an architecture with a dual pathway for a brain tumor and ischemic stroke segmentation, which processes a 3D Fully connected Conditional Random Field (CRF) to remove false positives. To overcome the computational load of processing 3D medical scans, they created a dense training scheme that is effective and efficient for processing 3D medical scans. They merge the processing of nearby image patches into one network pass and automatically adapt to the natural class imbalance in the data. They obtain an average dice coefficient equal to 69%.

Additionally, Liang et al. [10] introduced a framework to segment stroke lesions with DWI sequences that are based on two CNNs. One is a combination of two DeconvNets, which is the EDD Net; the other CNN is the multi-scale convolutional label evaluation net (MUSCLE Net), which aims to assess the lesions detected by the EDD Net and eliminate possible false positives. They tested their method on a large dataset including 741 subjects from DWI. The mean accuracy achieved is 67% in total. The mean Dice scores for subjects with only small and large lesions are 61% and 83%, respectively.

Zhiyang et al. [11] suggested a residual structured fully convolutional network (Res-FCN) based on 2D slices from DWI, ADC, and T2 WI. The suggested Res-FCN is trained and tested on ISLES 2015-SISS with 212 clinically acquired MRIs, which achieves a mean dice coefficient of 64.5% with a mean number of false negative lesions of 1.515 per subject.

Furthermore, Rongzhao et al. [12] used 3D contextual information and automatically learned features to propose an end-to-end model. To alleviate the hardness of training deep 3D CNN, they equipped the network with dense connectivity to allow the unimpeded propagation of information and gradients throughout the network. The Dice objective function was used to train the model to deal with the severe class imbalance problem in data. The model was built up with a DWI dataset with 242 subjects regrouped as 90 for training, 62 for validation, and 90 for testing. It achieved a Dice similarity coefficient, lesion-wise precision, and lesion-wise F1 score equal to 79.13%, 92.67%, and 89.25% respectively.

In 2019, Liangliang et al. [13] proposed a multi-kernel DCNN (MK_DCNN) composed of two symmetrical deep sub-networks, in which dense block are used to reduce the overfitting problem of deep networks such as the extraction of effective features from sparse pixels. A multi-kernel and the dropout regularization method were used to split the network into two sub-networks for getting more sensory fields, and the dropout regularization method to achieve an effective feature mapping respectively. Then, they applied median filtering to reduce noise and preserve image edge detail. The developed architecture provided a dice coefficient of 57%, a symmetric surface distance value average equal to 2.01mm, and a Hausdroff distance equal to 2.38 mm with the SISS challenge dataset. With the same challenge, Amish et al. [14] created a modified U-Net model and a multi-path network. The model obtained an average dice coefficient of 70.07%, a sensitivity value of 49.28%, a specificity equal to 99.78%, and a precision of 98.72%.

In the same year, to perform segmentation, a model for the spatial arrangement of pixels preserved by learning the local characteristics of an image was proposed by Karthik et al. [15]. This research work presented a supervised fully convolutional network (FCN). The remarkable point of this research is the application of Leaky Rectified Linear Unit activation in the last two layers of the network for precise reconstruction of the ischemic lesion. This allows the network to learn from additional features that are not considered in the existing U-Net architecture. An average segmentation dice coefficient of 70% was obtained with ADAM optimizer based on experiments carried out on the ISLES 2015 dataset only on axial plane slices [15].

In 2020, Liangliang et al. [16] presented a Res-CNN based on a U-shaped structure and integrated the residential unit dual in the network to alleviate the degradation problem. Fusion methods and data augmentation were used before training the model to expand their dataset. The presented model obtained an average dice coefficient equal to 74.20% and a Hausdroff distance equal to 2.33mm. It's the same for Amish et al. [17] have also continued research on this topic. They proposed a new architecture based on the Classifier-Segmenter (CS-Net), which involves a hybrid learning strategy with a self-similar U-Net model, explicitly designed to perform the segmentation task. The advantage is to develop a cascade architecture, which improves the precision while removing redundant parts of the Segmenter's input. With the ISLES SISS-2015 dataset, they achieved a dice coefficient, a precision, and a recall of 63%, 74%, and 62% respectively. With ISLES 2017, they obtained a dice coefficient, a precision value, and a recall of 28%, 37%, and 45%, respectively.

Zhang et al. [18] presented a framework to quickly and automatically segment stroke lesions on DWI. First, they designed a detection and segmentation (DSN) to address data imbalance. Second, they proposed a triple-branch DSN architecture, which was used to extract the different features. Third, they developed a multi-plane fusion network (MPFN), which aimed to make the final prediction more accurate. The authors tested their methods on the ISLES 2015 SSIS DWI sequence dataset. Experimentally, they obtained dice coefficient and sensitivity values of 62.2% and 71.7%, respectively.

Liangliang et al. [19] have continued research on this contribution, now with a third approach after the two mentioned previously. In this point, a new network neural convolutional deep residual attention (DRANet) was proposed to accurately

TABLE I. Summary of Existing Methods for MRI Images Segmentation

Authors	**Methods**	**Dice Coefficient(%)**	**Accurracy(%)**	**Precision (%)**
Kamnitsas et al. [9] (2017)	CRF	69	–	–
Liang et al.[10] (2017)	MUSCLE Net	61	67	–
Zhiyang et al.[11] (2018) (	Res-FCN	64.5	–	–
Rongzhao et al. [12] (2018)	3D CNN	79.13	–	92.67
Liangliang et al. [13] (2019)	MK-DCNN	57	–	–
Amish et al. [14] (2019)	UNet with multi-patchnetwork	70.07	–	98.72
Karthik et al.[15] (2019)	FCN	70	–	
Liangliang et al. [16] (2020)	Res-CNN	74.2	–	–
Amish et al. [17](2020)	CS-Net	63	–	74
Zhang et al. [18] (2020)	Multi-plane fusion network	62.2	–	–
Liangliang et al. [19] (2020)	DRANet	76	–	–
Aboudi et al.[20] (2022)	Unet	55.77	99.96	–
Aboudi et al.[21] (2022)	Hybrid ResNet50-Unet	64.14	99.43	–

and simultaneously segment and quantify lesions of stroke and white matter hyperintensity (WMH) in MRI images. Their solution's key architectural features are the use of the residual block and the Dice loss function to make the network training effective, as well as the use of the attention modules to produce a high-quality representation of the input images inside the network. Their proposed DRANET model obtains high-quality features from the input images. DRANet was trained and evaluated on 742 2D MRI images which are generated from (SISS) challenge and their approach achieves a dice coefficient of 76%.

Recently, Aboudi et al. [20], [21] developed two contributions to this idea. The first consists of developing a deep convolutional neural network (CNN) method inspired by the U-Net architecture. They applied a finetuning technique to adapt the U-Net architecture to our objectives. They evaluated her method on the public dataset ISLES 2015. Their model achieved a Dice Coefficient (DC) and accuracy equal to 55.77%, and 99.96% respectively. The second research consists of combining the UNet model with a pre-trained ResNet50 architecture to form a hybrid framework. They apply data augmentation techniques to improve the model's accuracy. They trained and tested their method on the ISLES 2015 dataset. The experimental results show the effectiveness of our method, which achieves a 99.43% average accuracy, and a 64.14% Dice Coefficient(DC).

The assessment of existing surveys underscores the rapid evolution of approaches in medical imaging, leveraging the capabilities of machine learning (ML) and deep learning (DL). While DL models, particularly CNNs, have shown substantial promise, persistent challenges and limitations have been identified. This observation prompts the introduction of attention mechanisms, such as CBAM, in our approach. Existing studies, including models like U-Net, have demonstrated success in brain ischemic lesion segmentation. However, issues like class balance, false positives, and effective 3D data processing persist. Noteworthy models like Res-FCN, Res-CNN, and innovative approaches like DRANet with attention modules

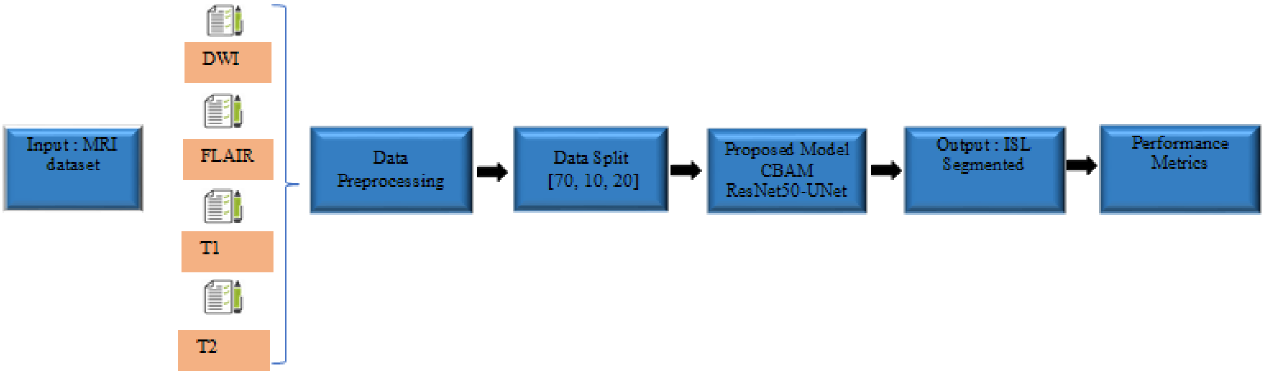

Fig. 1. Flowchart of the proposed approach.

have showcased impressive results. The summary Table I of existing methods highlights diverse approaches and metrics like Dice coefficient, precision, and accuracy. Despite these advancements, limitations in terms of precision and sensitivity justify the need for our CBAM-based approach and attention mechanism to address persistent challenges in accurate brain ischemic lesion segmentation. In essence, the analysis of past works underscores progress but emphasizes the ongoing need for improvements, justifying the introduction of attention mechanisms in our proposed approach.

III. Motivations and Contributions

In this research, we propose an attention model to enhance the performance of ISL segmentation. Only a handful of publications have explored the integration of attention block in segmentation models. Many researchers focus on improving the segmentation outcome without considering task efficiency. Thus, the most crucial aspect in any ML or DL models is to extract minimal yet valuable features. To address this issue, we will apply an attention-based mechanism to select relevant features from the entire MRI and use them for segmentation. Additionally, to minimize the algorithmic and computational complexity of the task, we will employ transfer learning instead of training a complete neural network from scratch, pre-trained with ResNet-50. This technique helps us improve segmentation performance while maintaining task accuracy. Therefore, we summarise our main contributions in this research paper as follows:

- An advanced CAD system for ischemic stroke brain segmentation based on CBAM and a hybrid ResNet50-Unet model from MRI sequences (DWI, T1, T2, and Flair) was developed.
- CBAM block was integrated after each convolution block into the ResNet50-UNet architecture to enhance the model performance and to enhance feature representation by emphasizing relevant channels and adjusting spatial perception.
- Significance evaluation of predicted ground truth for ISL segmentation in MRI sequences.

IV. Proposed Method

In this section, we provide a detailed explanation of the proposed CAD system for ischemic stroke brain segmentation, which relies on CBAM and a hybrid ResNet50-Unet model applied to MRI sequences (DWI, T1, T2, and Flair). Firstly, we present the dataset description and preprocessing steps. Subsequently, we delve into the detailed information about the architecture of the proposed CBAM ResNet50-Unet model. We also elaborate on the reasons for selecting this specific method. Fig. 1 illustrates an overview of our approach.

A. Dataset Description

The multimodal Ischemic Stroke Lesion Segmentation Challenge (ISLES) 2015, provided by the University Medical Center Schleswig Holstein (UKSH) Germany and the departments of Neuroradiology Hospital Rechts der Isar in Munich was used to perform this research study. The data acquisition parameters encompass a slice thickness of 5 mm, an echo time of 87 ms, and a repetition time of 3200 ms. ISLES 2015 dataset is reorganized as follows: SISS, which was employed in our work and involved segmenting sub-acute ischemic stroke lesions, and SPES, which involves estimating the stroke penumbra. This work uses a training dataset supplied by SISS that consists of 28 subject cases and a manually segmented and annotated ground truth. This dataset was acquired from 3T Philips systems and arranged into weighted-T1(T1), weighted-T2(T2), FLAIR, and DWI(b=1000) sequences with 57 to 154 slices. We have obtained a total of 4312 images. Fig. 2 illustrates an example of the four methods of MRI images. Each subject's data is represented in NIFTI(.nii) format, featuring an image shape of 240x240x155x3.

B. Preprocessing

The raw MRI images underwent preprocessing before being employed as input in our proposed approach. Each pixel from the original 3D images is converted into a series of 2D images. To enhance the dataset, non-relevant black images are removed, as they do not fall within the brain tumor category, and utilizing the entire image is unnecessary for medical image analysis. During the preprocessing step, images with black slices lacking information are excluded. Our focus centers on eight slices, commencing from slice 22, where

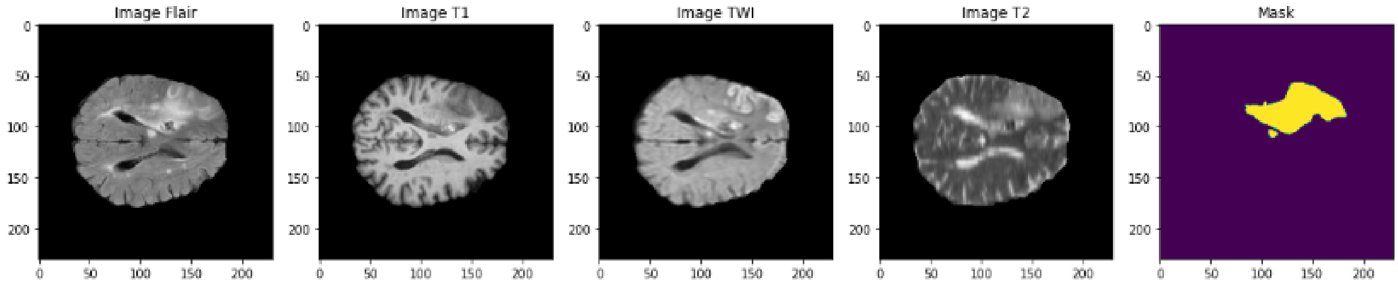

Fig. 2. The four MR image modalities are displayed, including Flair, DWI, T1, T2, and ground truth examples.

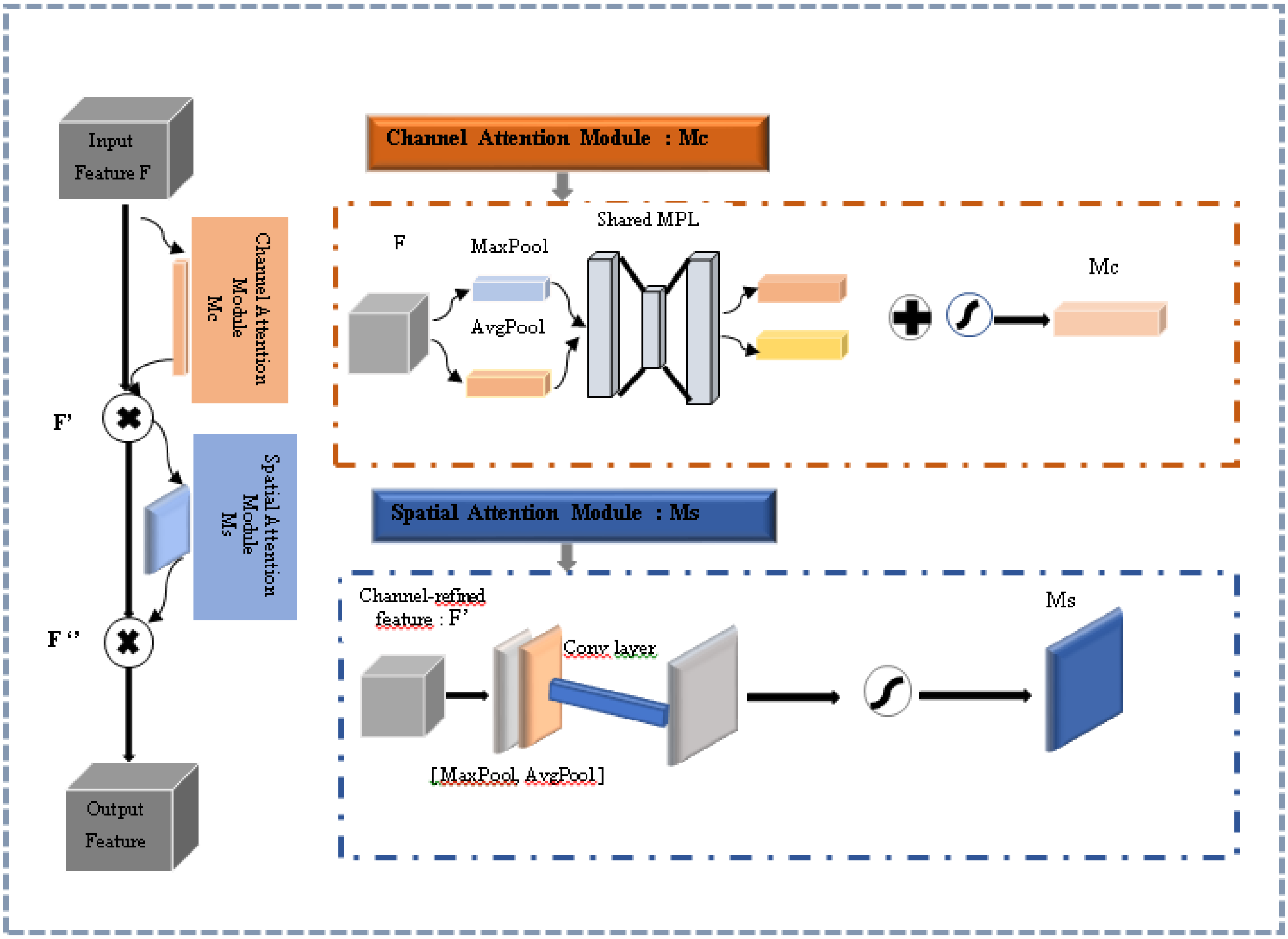
Input Feature F
Channel Attention Module Mc
F'
Spatial Attention Module Ms
F ''
Output Feature
Channel Attention Module : Mc
Shared MPL
F
MaxPool
AvgPool
Mc
Spatial Attention Module : Ms
Channel-refined feature : F'
Conv layer
Ms
[MaxPool, AvgPool]

Fig. 3. Architecture of the CBAM block.

we define our Regions of Interest (ROIs). Additionally, all images undergo resizing to 128x128x3, ensuring uniformity in dimensionality. The dataset is partitioned into distinct subsets: 70% for training, 20% for validation, and 10% for testing.

C. CBAM Model

CBAM, introduced by Woo et al., serves as an attention module designed to facilitate channel size and spatial operations within CNN architectures. This module comprises two blocks(modules): the channel attention module and the spatial attention module. Fig. 3 describes the CBAM block architecture.

1) Channel Attention Module: Channel attention focuses on discerning the meaningful content within an input image, determining 'what' features are significant. This is achieved by analyzing inter-channel relationships to enhance feature selection and extraction while minimizing loss values. The calculation of channel attention involves compressing the spatial dimension of the input feature map. To aggregate spatial information, Global Average Pooling (GAP) and max-pooling layers are employed. GAP obtained the aggregate information(calculating the average for each patch of the feature map) when the max-pooling layer reached the differences of features(calculates the maximum). The fusion of the GAP layer and max-pooling layer performed better than using a single layer to produce a weighted channel descriptor (Fig. 5). Channel attention is calculated as follows:
$M_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F)))$

$$= \sigma(W_1(W_0(F_c^{avp})) + W_1(W_0(F_c^{max})))$$

where F_c^{avp} and F_c^{max} denote the squeezed feature maps of the two pooling layers, σ represents the sigmoid function, $W_0 \in R^{r/C*C}$ and $W_1 \in R^{C*C/r}$ represent the weights of MLP.

2) Spatial Attention Module: It is based on 'where' is a relevant part. This module used the inter-spatial relationship between features to calculate the spatial attention map. Firstly, GAP and max-pooling functions are applied on the feature maps generated during the previous step (channel attention module) and squeezed into 2D features maps: $F_{avg}^s \in R^{1*H*W}$ and $F_{max}^s \in R^{1*H*W}$. After that, a convolution layer is added on the recombined two 2D feature maps to generate an efficiency feature maps. Then, a sigmoid function is used to calcule the spatial attention map $M_s(F) \in R^{H*W}$. Spatial attention is calculated as follows:
$M_s(F) = \sigma(f^{7x7}([AvpPool(F); MaxPool(F)]))$

$$= \sigma(f^{7x7}([F_{avg}^s; F_{max}^s]))$$

when σ is a sigmoid function and f^{7x7} denotes une convolution function with filter size of $7x7$.

In Spatial Attention Module, GAP and max pooling functions are used to generate spatial feature descriptor then a $7x7$ convolution filter used to emphasize a spatial information.

D. Pre-trained ResNet50 Model

ResNet50 stands as a prominent member of the Residual Network family architecture and is currently among the most widely utilized models in the field of image recognition. It was introduced by Kaiming He et al.[22] in their influential paper "Deep Residual Learning for Image Recognition. ResNet50 has demonstrated exceptional performance across diverse vision applications, encompassing tasks such as classification, object detection, and semantic segmentation. Fig. 4 illustrates the ResNet50 architecture. It comprises 48 convolutional layers organized into four stages, featuring residual blocks with shortcut connections to address the challenges of training very deep. ResNet50 effectively addresses the vanishing gradient problem. The architecture's bottleneck design optimizes computational efficiency, incorporating 1x1 convolutions for feature map dimensionality reduction. With Global Average Pooling (GAP) as a concluding layer and pre-trained weights often obtained from datasets like ImageNet, ResNet50 stands out for its ability to provide compact representations and serve as a robust foundation for transfer learning. This model's advantages encompass its proficiency in mitigating training challenges, its adaptability to diverse computer vision tasks, and its consistent delivery of state-of-the-art performance in image classification and segmentation.

The pre-trained ResNet50 model comprises four key blocks, each referred to as a stage. The initial block involves data preprocessing and feature extraction, followed by three residual blocks within different stages. These residual blocks, incorporating multiple convolutional layers, contribute to the network's depth and capacity to capture intricate features. This architecture, known for its efficacy in image recognition, has achieved state-of-the-art results in various visual tasks due to its depth, skip connections, and the ability to train deep networks effectively.

E. Unet Model

UNet model stands as the common model choice for segmentation tasks in the medical imaging domain, such as segmenting organs or tumors in medical scans. It was developed by Olaf Ronneberger, Philipp Fischer, and Thomas Brox, U-Net is characterized by a U-shaped architecture, featuring an encoder pathway and a symmetric decoder pathway. It adeptly gathers low-level features that encapsulate information about the shapes of different classes, alongside high-level features that leverage this information to discern the class to which each position belongs. The architecture seamlessly integrates both low-level and high-level features to reconstruct the original input's spatial dimensions, ensuring precise classification for each location. UNet architecture is comprised of two fundamental blocks: the encoder and the decoder. The encoder captures contextual information through downsampling, while the decoder reconstructs the segmented image with fine-grained details using upsampling. The unique aspect of U-Net is the incorporation of skip connections that connect corresponding layers between the encoder and decoder, aiding in the precise localization of segmented objects. U-Net's ability to handle limited labeled data and its effectiveness in preserving spatial information makes it a popular choice for image segmentation tasks.

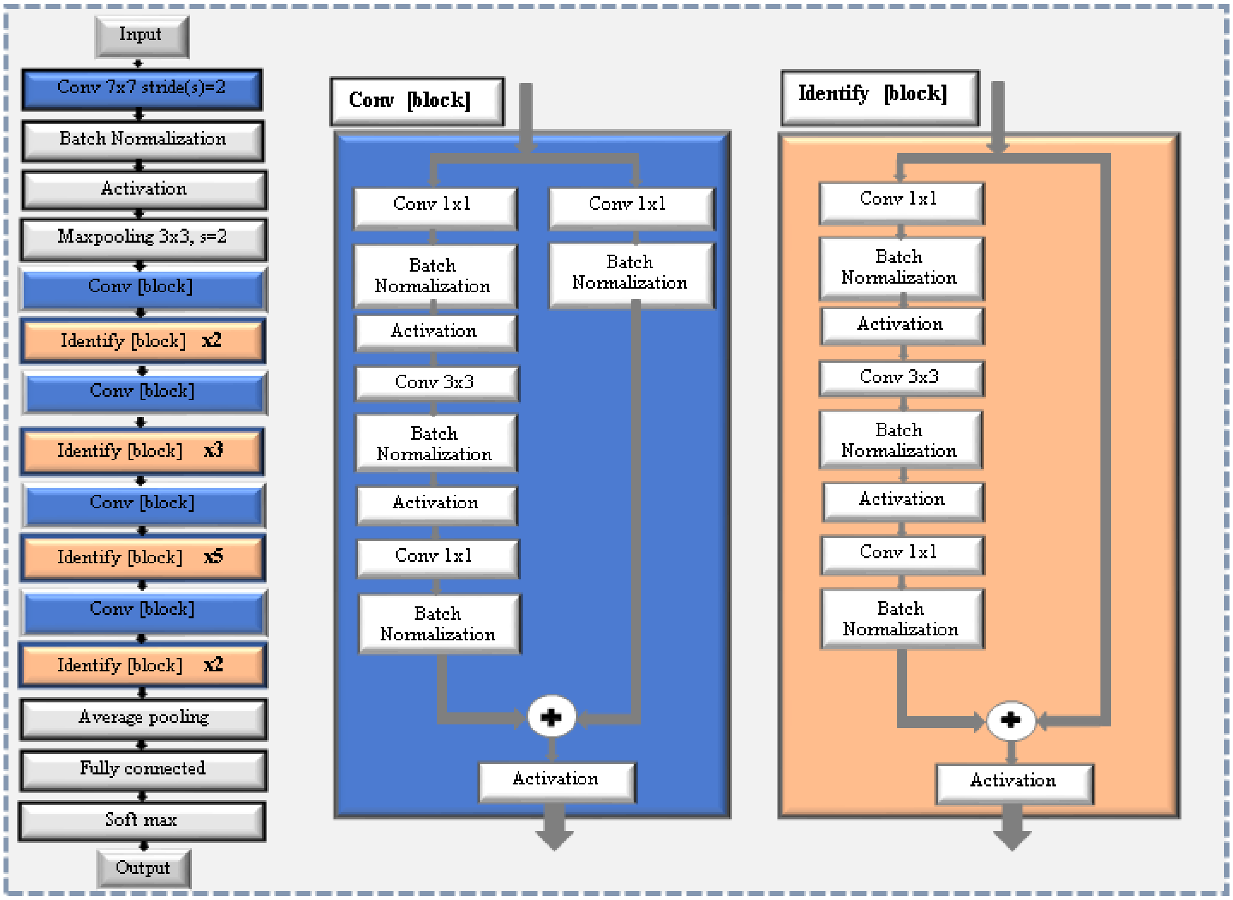

Fig. 4. The architecture of the pre-trained ResNet50 model.

F. Proposed Hybrid CBAM ResNet50-Unet Model

The UNet model architecture is organized into two primary blocks: the encoder and the decoder. In the encoder network, the input is processed through successive convolutional blocks, each succeeded by max-pooling layers for downsampling. These blocks progressively extract hierarchical features, capturing both low-level and high-level representations of the input. Subsequently, the decoder network begins with upsampling operations using transposed convolutions (Conv2DTranspose). Each upsampling step is accompanied by concatenation with the corresponding feature maps from the encoder, creating skip connections. Convolutional blocks in the decoder then process this concatenated information, gradually restoring the spatial dimensions of the original input. The final layer, utilizes a 1x1 convolution with softmax activation, producing a pixel-wise classification map. This architecture seamlessly integrates the encoding of input features and the decoding of spatial information, making it well-suited for segmentation tasks.

The backbone of the ResNet50 model is added into the encoder bloc only. We freeze the encoder layer using fine-tuning and transfer learning in the pre-trained ResNet50 model, entrain the absence of an update of weighted layer during the execution of training data. Instead, the weight of the convolutional layer off ResNet50 will be used. First, we modified the architecture of the ResNet50 to be similar to UNet, adding an expanding layer composed of multiple up-sampling layers and convolution layers at the end of her structure. Second, this is carried out up until the model's overall architecture is symmetric and takes the form shape of a U-Net. Such as this combination the trainable parameters models will be reduced. After, we train the input data MRI using the two proposed hybrid models with a transfer learning method.

In this approach, CBAM block has been thoughtfully incorporated after each convolutional block in the model. Each convolutional block consists of a sequence of convolutional layers, followed by a dropout operation, and finally, batch normalization. The novelty lies in adding the CBAM module after this layer sequence, designed to enhance feature representation by emphasizing relevant channels and adjusting spatial perception. This approach strengthens the model's ability to capture meaningful information while preserving spatial coherence. The addition of the CBAM module after each convolutional block contributes to enhancing the model's performance, especially in image segmentation tasks where the accuracy of representations is crucial. The method allows for the selective integration of attention mechanisms throughout the network, which can be beneficial for the model's prediction quality.

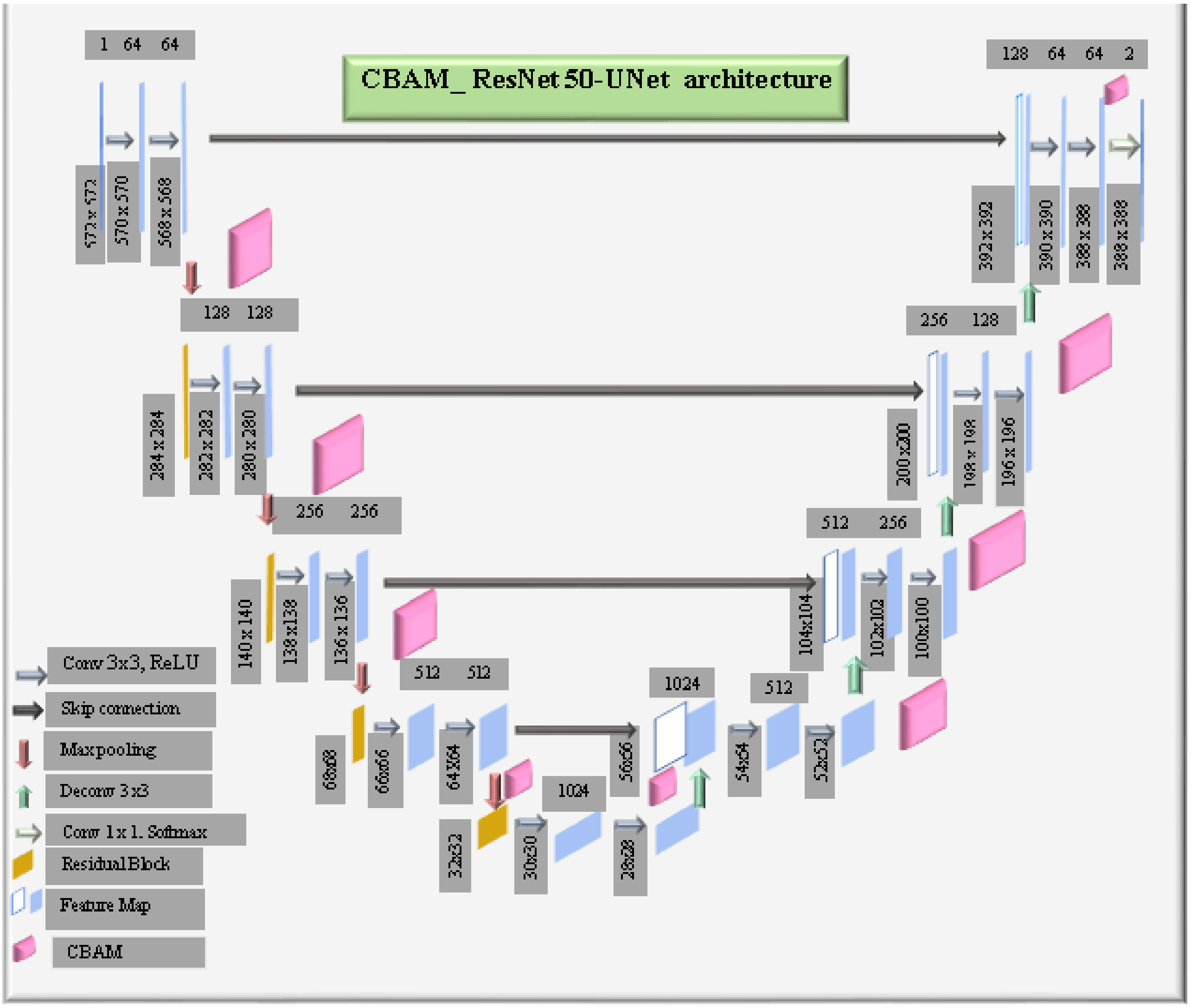

Fig. 5. The detailed architecture of the CBAM ResNet50-Unet model.

V. Experimental Results and Discussion

This section highlights the obtained experimental findings using our model based on CBAM ResNet50-Unet to segment the Ischemic Stroke Lesion tested on the ISLES 2015 MRI images.

A. Implementation Details

The experiments were conducted using the Python language in the Ubuntu environment on a Dell computer equipped with an Intel Core i5 8th generation processor and 8 GB of RAM. The system also featured an NVIDIA GeForce GTX 1050 graphics card with NVIDIA Driver Version 440.59, and the Kaggle framework was utilized. Keras and TensorFlow served as the primary frameworks for implementing the architecture.

To create the optimal model, various variables have been tested and the most effective parameters are chosen. The proposed CBAM ResNet50-UNet architecture was trained with the following parameters: a batch size of 32, 100 epochs, stochastic gradient descent (SGD) optimizer with a learning rate of 0.00001, momentum set to 0.9, and number of epochs of 100. The binary cross-entropy loss function was plotted against the epoch number, and a categorical cross-entropy loss function was also employed.

B. Evaluation Metrics

To assess the efficacy of our approach, the Dice Coefficient (DC) was employed as the primary metric, as well as specificity, sensitivity, precision, and recall. DC quantifies the spatial overlap between the automatically generated segmentation output and the ground truth. Specificity gauges the network's proficiency in predicting healthy tissues, while sensitivity evaluates its ability to identify lesions accurately. Precision, also known as positive predictive value, measures the proportion of relevant outcomes among the predicted positive instances. Accuracy serves as a measure of the overall effectiveness of the proposed approach, capturing the ratio of correct predictions to the total instances. Additionally, recall assesses the model's capability to correctly classify the total

TABLE II. A COMPARISON OF OUR APPROACH AND STATE-OF-THE-ART METHODS TESTED ON THE ISLES 2015 DATASET

Authors	**Methods**	**Dice Coefficient(%)**	**Accurracy(%)**	**Precision (%)**
Kamnitsas et al. [9] (2017)	CRF	69	–	–
Rongzhao et al. [12] (2018)	3D CNN	79.13	–	92.67
Liangliang et al. [13] (2019)	MK-DCNN	57	–	–
Amish et al. [14] (2019)	UNet with multi-patchnetwork	70.07	–	98.72
Zhang et al. [18] (2020)	Multi-plane fusion network	62.2	–	–
Liangliang et al. [19] (2020)	DRANet	76	–	–
Aboudi et al.[20] (2022)	Unet	55.77	99.96	–
Aboudi et al.[21] (2022)	Hybrid ResNet50-Unet	64.14	99.43	–
Our approach	**CBAM ResNet50-Unet**	**79.6**	**99.56**	**97.12**

relevant results. This comprehensive set of metrics provides a thorough evaluation of the performance of the proposed approach across various aspects of segmentation quality and predictive accuracy. These metrics are defined as [23]:

$$DC = \frac{2TP}{2TP+FP+FN},$$

$$Accuracy = \frac{TP+FP}{TP+FP+TN+FN},$$

$$Precision = \frac{TP}{TP+FP},$$

where : TP = True Positive , FP = False Positive, FN = False Negative, and TN = True Negative

C. Experimental Results

The proposed hybrid model, CBAM ResNet50-UNet, leverages the advantages of transfer learning with a ResNet50 model to enhance performance, particularly in overcoming the challenges associated with a small dataset. The use of a pretrained ResNet50 model allows for the transfer of knowledge from a large dataset to our specific problem domain, aiding in faster convergence and improved accuracy. Moreover, to further boost the model's capabilities, CBAM is incorporated after each convolutional block. CBAM enhances feature discriminability by capturing both spatial and channel-wise attention. This addition helps the model focus on important features, promoting better segmentation results. UNet being a complex architecture, typically demands a substantial amount of training time, and its performance can be influenced by computer specifications. The integration of CBAM aims to address these challenges, making the proposed hybrid model more efficient in handling segmentation tasks. During experimentation, various scenarios were tested to identify the optimal model based on loss and accuracy metrics. Additionally, we calculated DC, precision, and accuracy values to comprehensively compare the segmentation results of the model with the ground truth values, demonstrating the effectiveness of the proposed approach.

Our proposed approach, CBAM ResNet50-UNet is tested on the ISLES 2015 dataset. Fig. 7 and 8 illustrated an example of prediction outputs and ground truth comparisons for the CBAM ResNet50-Unet model applied to the DWI and T2 sequences. These figures provide a comprehensive visual representation of the model's performance in accurately delineating lesions in each sequence, highlighting the efficacy of our segmentation approach.

Fig. 6 visually presents the performance metrics, including accuracy and loss, to provide a comprehensive evaluation of the proposed method. These curves offer a detailed insight into

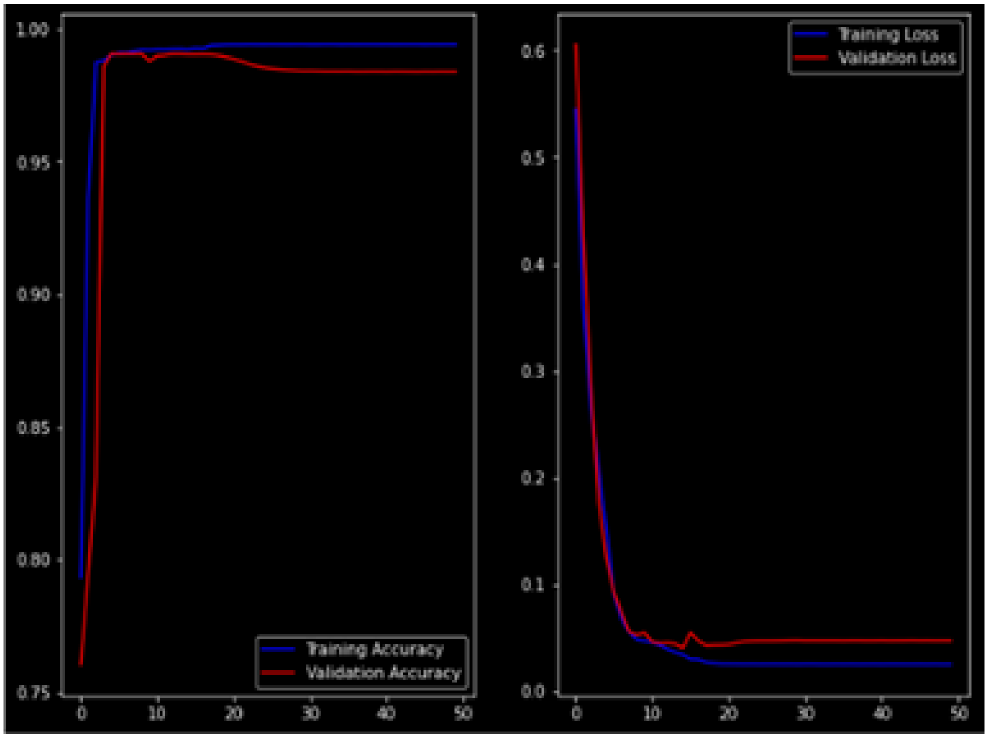

Fig. 6. Training and validation curves of accuracy and loss metrics for the CBAM ResNet50-Unet model.

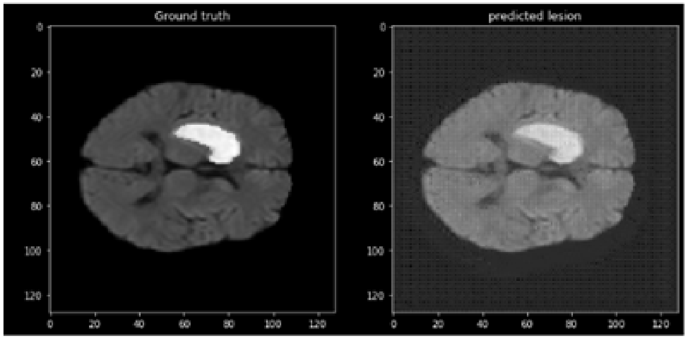

Fig. 7. Prediction outputs and ground truth comparisons for the CBAM ResNet50-Unet model applied to the DWI sequence.

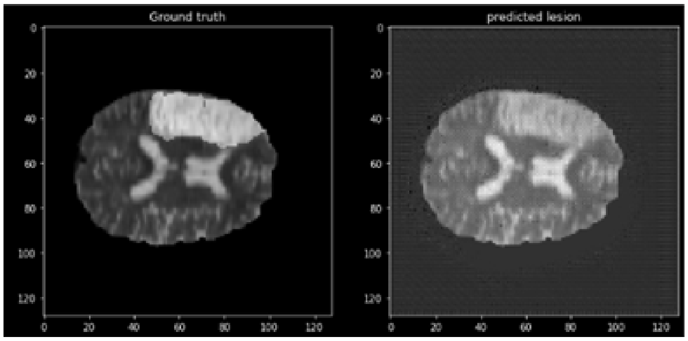

Fig. 8. Prediction outputs and ground truth comparisons for the CBAM ResNet50-Unet model applied to the T2 sequence.

how the model evolves over iterations, illustrating its capability to achieve accurate predictions, minimize loss, and optimize segmentation quality, thereby supporting the effectiveness and robustness of our proposed approach.

D. Comparison with State of the Art Studies

Table II compares the proposed model with state-of-the-art models that were trained on the ISLES 2015 dataset. Our CBAM ResNet50-Unet model stands out with a Dice Coefficient of 79.6%, an accuracy of 99.56%, and a precision of 97.12%. These results surpass the performance of numerous state-of-the-art approaches, highlighting the effectiveness of our model in predicting ISL MRI sequence outputs.

E. Discussion

This study presents our new approach CBAM ResNet50-UNet model for the segmentation of medical images, particularly focusing on lesions in the context of ISL segmentation. Through extensive experimentation and evaluation on the ISLES 2015 dataset, our proposed model has demonstrated remarkable performance, outperforming four state-of-the-art models in terms of accuracy, loss, and DC.

The integration of transfer learning with a pre-trained ResNet50 model, coupled with the incorporation of CBAM after each convolution block, has proven to be pivotal in enhancing the model's ability to discern intricate features and optimize segmentation accuracy. The visual representation in Fig. 10 and 9 showcases the model's efficacy in accurately delineating lesions across multiple sequences.

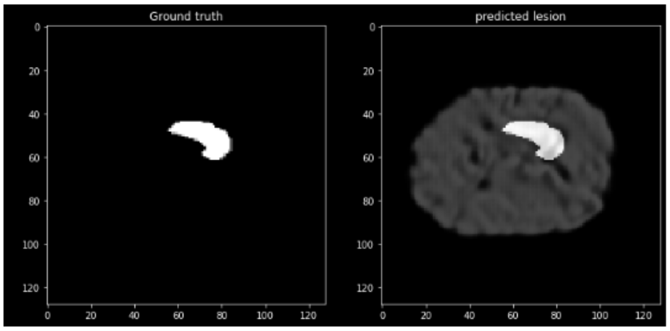

Fig. 9. Example 1 of prediction outputs and ground truth comparisons for the CBAM ResNet50-Unet model.

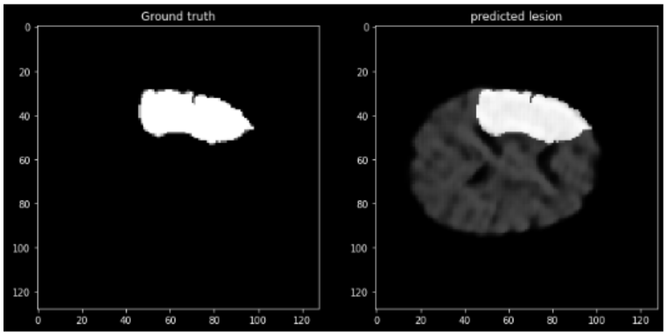

Fig. 10. Example 2 of prediction outputs and ground truth comparisons for the CBAM ResNet50-Unet model.

Moreover, the comprehensive analysis presented in Table II underscores the superiority of our proposed model in comparison to existing approaches. The achieved results not only validate the effectiveness of our methodology but also signify its potential for real-world applications in ischemic stroke lesions detection.

As illustrated in Fig. 11, our proposed CBAM Resnet50-UNet model, when evaluated on the ISLES 2015 dataset, demonstrated notable performance metrics. Specifically, it achieved a Dice coefficient of 79.6 %, an accuracy of 99.6 %, and a precision value of 97.1 %. Comparing these results to existing methods incorporating CRF, 3D CNN, MK-DCNN, UNet with multi-patch network, DRANet, Unet, and Hybrid ResNet50-Unet, our model outperformed them with Dice coefficients of 69 %, 79.1 %, 57 %, 70.7 %, 62.2 %, 76 %, 55.8 %, and 64.1 %, respectively. In terms of accuracy, our model achieved a significantly higher value of 99.9 %, surpassing all previous related works. Notably, Aboudi et al. reported an accuracy of 99.9 % in 2022, whereas their earlier works in the same year recorded values of 99.4 % and 99.7 %. Additionally, while the precision in model [14] reached 98.7 %, our CBAM ResNet50-Unet demonstrated a commendable precision value of 97.1 %

VI. Conclusion

In conclusion, this research paper introduces a novel CAD system for ischemic stroke brain segmentation in MRI sequences, integrating CBAM and a hybrid ResNet50-Unet model. Our motivation stems from the need to enhance both segmentation outcomes and task efficiency. The developed CAD system demonstrates promising results on the multimodal ISLES 2015 dataset, achieving a Dice Coefficient of 79.6% and a precision value of 97.12%. The integration of the CBAM block into the ResNet50-Unet architecture gives our model greater spatial awareness and adaptability to complex anatomical structures, enhances feature selection and extraction, and improves feature representation and segmentation accuracy. These findings contribute significantly to the field of ischemic stroke brain segmentation, laying the foundation for future work in unsupervised segmentation models and further refinement of attention mechanisms within our system.

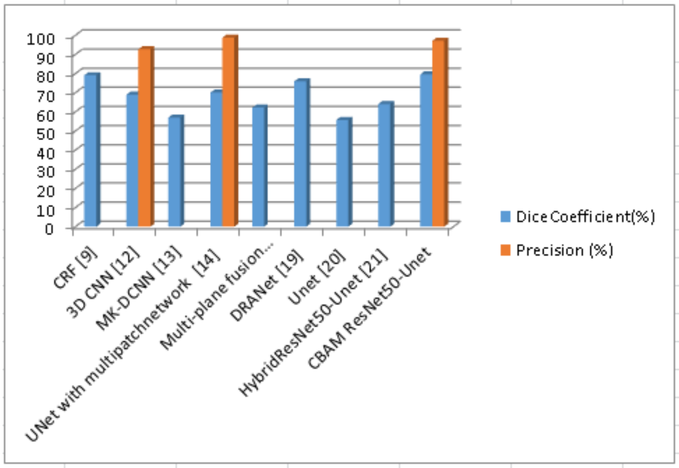

Fig. 11. Proposed CBAM Resnet50-UNet model.

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Optimizing Bandwidth Reservation Decision Time in Vehicular Networks using Batched LSTM

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***Abstract*—Time-sensitive and safety-critical networked vehicular applications, such as autonomous driving, require deterministic guaranteed resources. This is achieved through advanced individual bandwidth reservations. The efficient timing of a vehicle decision to place a cost-efficient reservation request is crucial, as vehicles typically lack sufficient information about future bandwidth resource availability and costs. Predicting bandwidth costs often using time-series machine learning models like Long Short-Term Memory (LSTM). However, standard LSTM models typically require longer durations of multiple input data sets to achieve high accuracy. In certain scenarios, quick decisions must be made, even if the vehicle means sacrificing some accuracy. We propose a batched LSTM model to assist vehicles in placing bandwidth reservation requests within a limited data for an upcoming driving path. The model divides data during training to enhance computational efficiency and model performance. We validated our model using historical Amazon price data, providing a real-world scenario for experiment. The results demonstrate that the batched LSTM model not only achieves higher accuracy within a short input data duration but also significantly reduces bandwidth costs by up to 27% compared to traditional time-series machine learning models.**

***Keywords*—Networked vehicular application; time-sensitive networking; network reservation; batched LSTM**

I. Introduction

In recent years, significant efforts have been made by academia and industry to leverage powerful onboard computing resources for applications such as self-driving [1], [2]. These applications are typically computation-intensive, safety-critical, and time-sensitive, requiring immediate action and reaction to ensure safety. However, the limited onboard computing resources of a single vehicle may not be sufficient to handle the demands of these applications. To address this, application data can be offloaded to cloud servers or edge cloud servers via 5G Vehicle-to-Infrastructure (V2I) connections [3], [4]. A prominent challenge is the execution of computation-intensive tasks within strict time constraints, often with a maximum latency threshold of 100 ms $\sim 1s$ [5].

To ensure the essential network resource requirements (i.e., bandwidth) between vehicles and fog/edge networks for safety, a reservation approach is employed. This approach guarantees timely access to scarce bandwidth resources. The conventional approach, network-side reservation [6], [7], [8], involves the MNO allocating bandwidth for various Quality of Service (QoS) classes. However, this approach provides probabilistic rather than deterministic guarantees for individual vehicles accessing network bandwidth. Vehicle-side and individual bandwidth reservation has proven to be a more efficient solution, where vehicles reserve the necessary resources in advance and make reservations based on their specific requirements and resource costs rather than relying on the MNO to allocate resources on their behalf [9], [10], [11], [12], [13]. Another focus of this approach is the economical aspect, which is being minimized by the expenditure for guaranteed access to the network upon reservation.

From the viewpoint of business, MNOs have various traditional pricing options for allocating resources. These involve network service reservation (i.e., subscription) [14] and the Pay-As-You-Go (PAYG) option [15]. However, these pricing strategies may not always effectively manage peak-time and real-time network conditions while ensuring sufficient QoS. Recently, dynamic pricing has emerged as a promising solution for resource management in edge computing [16], [17]. This method dynamically adjusts prices based on network conditions, aiding in managing congestion and ensuring QoS. However, many individual reservation methods overlook dynamic pricing set by MNOs [9], [10], [11], leading to overpriced reservations or insufficient resources.

As a result, vehicles face various challenges, such as the timing of place reservation requests, leading to higher costs or missed opportunities for cost savings in this dynamic environment. Companies like Amazon Web Services (AWS), MTN, China Telecom, and Uninor utilize this method, adjusting prices in response to supply and demand [18], [19], [20]. In a prior study [12], we introduced a concept called a smart request, which is a strategically placed reservation request that allows vehicles to optimize bandwidth costs and mitigate potential risks associated with dynamic pricing and resource unavailability from MNOs. We employed machine learning techniques, specifically LSTM and Transformers, which have proven effective in temporal prediction tasks. However, the conventional LSTM model required a long time interval of input data to achieve high precision, which is not always feasible in some scenarios where vehicles often need to make quick decisions, even if it means sacrificing some accuracy.

To address this, we proposed the batched LSTM model. This model divides data into batches during the training process, which can help improve computational efficiency and model performance. It optimizes the decision time for bandwidth reservation requests within a multiple time interval for predicting bandwidth costs for an upcoming driving path. The major contributions of our article can be summarized as follows:

- We formulate the optimization problem for bandwidth reservation with the primary objective of minimizing the comprehensive cost over a specified time interval.

- We propose a batched LSTM model, which is utilized to optimize decision time by efficiently handling multiple requests concurrently within a short time.
- Through simulations based on the historical dataset of Amazon [18], we show that the proposed model achieves higher accuracy for a given time interval of data and also reduces bandwidth costs compared to traditional models.

The remaining sections of the paper have been arranged as follows: Section II reviews relevant work on cost-effective resource reservation. Section III covers the system model. Section IV provides a formulation for the bandwidth reservation problem. In Section V, we propose to optimize bandwidth reservation decision time and the implementation of the batched LSTM model in this work. In Section VI, we carry out a comparison of the performance of the proposed model with state-of-the-art methods. Section VII concludes the article.

II. Related Work

Many studies have explored problems in resource reservation, focusing on network-side resource reservation in mobile networks[6], [7]. However, few studies have considered the economic implications of vehicle-side reservations with a focus on minimizing resource consumer expenditure. This is becoming a growing area of interest in edge computing [9], [10], [11], [12], [13].

Generally, most studies related to reservation requests mainly put emphasis on the onsite competition [21],[22] or immediate request mode. The main difference between those two types of requests is that in competition requests, users compete for the resource through various game theoretic ways, such as auctions, Stackelberg game, etc. [21], [23], [22]. This results in only a limited number of winners acquiring the resources, leading to a risk of failure for some users and a violation of QoS. Furthermore, onsite requests frequently exhibit volatile pricing and inherent inequity due to the stochastic nature of resource availability and demand. In contrast, immediate requests, as discussed in [10], the authors developed an approach based on meta-learning to assist in reserving resources for computing with the goal of minimizing the cost of using edge services. Zang et al. proposed a smart online reservation framework to minimize the cost of reserving resources for an individual user [9] or multiple users [11]. Based upon their settings, the approaches discussed above for reservations mainly operate on an immediate request basis. As a result of limited resources, the corresponding vehicles need to carry out the schedule reservation well in advance in order to ensure they are able to acquire the necessary resources on time. As a consequence, the immediate requests entail high costs and low guarantees. Planning reservations efficiently is a challenge as users lack knowledge about cost trends and available resources, making it difficult to ensure cost-effectiveness.

Motivated by challenges incurred by competition and immediate requests, an advanced reservation solution [12] has been introduced. This solution enables the advanced reservation of mobility locations at specific time intervals, achieving commendable cost-effectiveness and time efficiency. However, this study lacks an in-depth discussion of the challenges and complexities associated with making reservation decisions within short time intervals. To enhance the reservation decision time, we leverage batched LSTM, which is often more effective for quick decisions with limited data than standard LSTM due to its ability to process multiple input sequences concurrently.

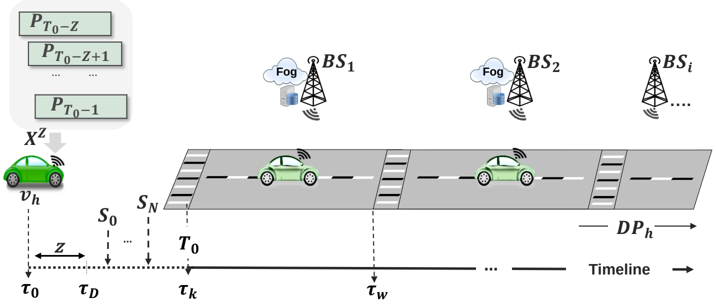


Fig. 1. System model.

III. System Model and Formulation Problem

A. System Model

In this paper, the urban vehicular network is composed of vehicles and Base Stations (BSs), which include Macro Base Stations (MBSs) and Road Side Units (RSUs). The driving path (DP) is partitioned into road segments (RS), each BS associated with a single MNO. This MNO establishes wireless connections between edge routers and participating vehicles within the core network. In each segment of the road, a BS is strategically located (Fig. 1).

In order to meet the strict latency demands of vehicular applications, a Fog/Edge server node is intricately integrated into the infrastructure of each BS. At the initial time τ_0, vehicle v_h $(h = 1, 2, ..., V)$ initiates a reservation request to the MNO for a specific RS along the DP_h. This request provides detailed information about the bandwidth time period Δt_h required to successfully traverse the intended DP_h.

The specified time duration, denoted as Δt_h, is carefully divided into reservation time intervals represented by the range $[\tau_k, \tau_w]$. Each of these intervals corresponds to a specific RS_i, which is entirely covered by a BS_i and the i^{th} road segment. τ_k denotes the entry time into the designated RS_i, while τ_w marks the exit time from that specific RS_i. The determination of these intervals depends on the length of DP_h and the speed of the vehicle v_h, both of which are computed based on data obtained from the navigation system.

Vehicle v_h divides its desired departure interval $[T_0, T_R]$ into $|St|$ small intervals, each representing a discrete time step. For each time step, vehicle v_h requests the cost associated with its designated route DP_h. The resulting list of costs, p_{T_0},..., p_{T_R}, forms a session (S_0). This process is repeated at regular intervals of Δt_{s_v}, up to a maximum of N times, resulting in a sequence of pricing sessions (S_0, S_1,..., S_N), as illustrated in Fig. 1. The session validity time (Δt_{s_v}) is the duration for which the pricing sessions remain valid. This is a predetermined parameter set by the MNO.

B. Formulation Problem

The optimization problem for bandwidth reservation aims to minimize the comprehensive cost associated with reserving bandwidth over the time interval $[\tau_k, \tau_w]$ for all RS_i in D_h. In this approach, the RS_i is transformed into discrete cost areas using a function φ. Each cost area, denoted as A, is associated with a time interval $[\tau_k, \tau_w]$.

$$\varphi : R_+^2 \to R_+^{N \times R} : (\tau_k, \tau_w) \mapsto A \tag{1}$$

where $R = T_R - T_0$ and A is a matrix holding the information about the prices:

$$A = \left[\begin{pmatrix} p_{11} & \cdots & p_{1R} \\ \vdots & \ddots & \vdots \\ p_{N1} & \cdots & p_{NR} \end{pmatrix} \right] \tag{2}$$

This matrix has S_N rows (representing sessions) and T_R columns (representing the desired time departure $[T_0, T_R]$), where $p_{n,r}$ denotes the price corresponding to the n-th session and the r-th desired departure time. The θ function is utilized to establish a relationship between a designated area A and its comprehensive reservation cost:

$$\theta : R_+^{N \times R} \to R_+ \tag{3}$$

Additionally, the function $\omega = \theta \circ \varphi$, where θ and φ are distinct functions, is used to map:

$$\omega : R_+^2 \to R_+ \tag{4}$$

Ultimately, the objective function J is formulated as follows:

$$J = \sum_{\tau_k, \tau_w} \omega(\tau_k, \tau_w) \tag{5}$$

The sum operates over all pairs (τ_k, τ_w) of start and end times. The function ω assigns these time intervals to an overall reservation cost based on the previously defined composite function, incorporating both φ and θ. The objective is to minimize this overarching objective function.

$$\min_{\tau_k, \tau_w} J(\tau_k, \tau_w) \tag{6}$$

The implementation of an optimization technique requires a sophisticated prediction model for accurate decision-making. The process begins with a proficient time-series model, ensuring high prediction accuracy. This forms the basis for effectively applying the optimization technique, using the insights from the prediction model to guide decisions. The model uses historical average prices, X^Z, from the interval $[T_0 - Z, T_0 - 1]$ (as per Eq. 7) to predict the price at time t. Here, Z is the number of time steps before the first price request (τ_D). Optimal Z values can be found by searching for a δt that yields satisfactory accuracy. Hence, the prediction model can be expressed as:

$$(\widehat{x}_{Z+1} = f\left(X^Z; \theta\right)) \tag{7}$$

where,

$$X^Z = [P_{T_0 - Z},\ P_{T_0 - Z + 1},\ \cdots\ P_{T_0 - 1}]$$

f is the model with trainable parameters θ, which returns the expected future price, $\widehat{P}_{T_0}$, for reserving in the following t time steps. The expected price $\widehat{P}_{T_0}$ is then pushed into X^Z, forming a constant size buffer as follows: $X^Z = \left[P_{T_0 - Z + 1}\ \cdots\ \widehat{P}_{T_0}\right]$. Subsequently, the value $\widehat{P}_{T_0+1}$ is obtained by repeating the process of predicting and updating the buffer. This process continues until the expected future price $\widehat{P}_{T_R}$ is obtained, as shown in Fig. 2. The method for finding the minimum expected price is as follows:

$$(\widetilde{p} = min(\widehat{P}_{T_0},\ \widehat{P}_{T_0+1},\ \cdots\ \widehat{P}_{T_R})) \tag{8}$$

In order to calculate the optimal reservation time, we introduce the concept of a decision threshold function, denoted as DE. This function uses the output (the expected minimum future price) to advise a vehicle on its reservation strategy. Specifically, it determines whether the vehicle should reserve at the minimum price in the current session (reserve) or consider postponing the reservation by requesting a new session (wait). The decision action is computed using Eq. (9):

$$DE = \begin{cases} reserve: & \widetilde{p}_{S_n} \leq \widetilde{p} - \varepsilon(n) \\ wait: & \text{otherwise} \end{cases} \tag{9}$$

where,

$$\varepsilon(n) = \frac{c}{n}\ ,\ n \in [1,\ N]$$

In our model, N represents the maximum number of sessions that can be requested. The hyper-parameter c should be tuned to maximize benefits. The expected minimum future price, denoted as $\widetilde{p}$, is derived from Eq. (8). Our model anticipates session prices for the time interval $[T_0, T_R]$. The term $\widetilde{p}_{S_n}$ represents the lowest price at the current requested session, which includes prices $\widetilde{p}^{S_n}_{T_0}, \widetilde{p}^{S_n}_{T_0+1}, \ldots, \widetilde{p}^{S_n}_{T_R}$ in the time interval $[T_0, T_R]$. This is defined in Equation (10):

$$(\widetilde{p}_{S_n} = min(\widetilde{p}^{S_n}_{T_0},\ \widetilde{p}^{S_n}_{T_0+1},\ \ \cdots\ \widetilde{p}^{S_n}_{T_R})) \tag{10}$$

The proposed model suggests the optimal reservation time for the vehicle by returning the time associated with the lowest price. The steps of this algorithm are detailed in Algorithm 1. In the context of Formula 9, determining the optimal risk level is of substantial importance. This is because the proposed strategy aims to minimize overall costs while reducing the risk of rejecting valid sessions. The goal is to find an optimal balance that maximizes efficiency and minimizes negative outcomes. This strategy is based on the concept that the risk is lower at the beginning, but as the maximum number of sessions is approached, the risk begins to increase. The

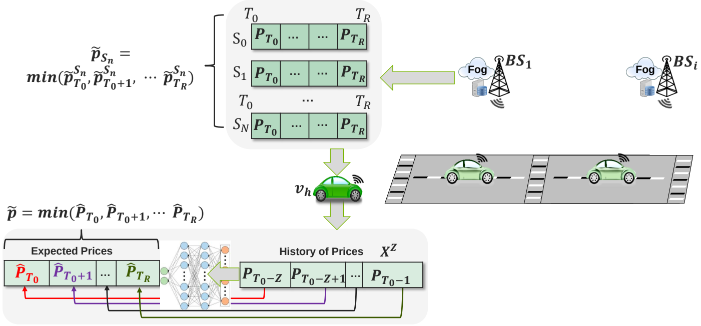


Fig. 2. Prediction model bandwidth reservation request timing.

decision function uses $\varepsilon(n)$ because the model predicts the expected price of reserving in the next time step δt, not the minimum price. Statistically, if the vehicle waits, it will receive a price that is at least equal to the expected price. However, there is a high chance of getting a lower price, and the amount of reduction depends on the variance in the prices. Therefore, the constant c should be proportional to the variance in the prices of DP_h. As the value of N is approached, $\varepsilon(n)$ should decrease. Here, N represents the maximum number of sessions that can be requested per time step δt, which is determined by the MNO. The value of $\varepsilon(n)$ also depends on the time the vehicle started searching for the minimum price prior to takeoff.

In our model, the constant c is crucial. Its optimal values are determined empirically, balancing cost savings and risk reduction. The choice of c also prevents failing to reserve resources due to reaching the maximum number of sessions. Further investigation of these values is conducted in our experiments.

IV. Bandwidth Reservation Decision Time

First, a brief overview of the approach is provided. Following that, appropriate time series prediction models are selected and applied. This enables vehicles to reserve bandwidth on a specific future path at a designated time, thereby minimizing costs. Subsequently, the prediction model, which utilizes the batched LSTM algorithm, is explained in detail.

A. *Overview on the Proposed Approach*

From the vehicle's perspective, the challenge lies in efficiently timing decisions for bandwidth reservation requests due to insufficient future price prediction data. The proposed approach involves vehicle v_h dividing its desired departure interval $[T_0, T_R]$ into Q small δt intervals. It then requests the cost for each area A of DP_h at each future time.

The proposed method uses a time-series deep neural network to predict future costs and continues to request pricing sessions until the minimum price surpasses a dynamic threshold. This threshold, determined by a parameter c, adjusts with each new session to balance risk. The prediction model, trained on models like LSTM and Transformers, leverages recurrent load patterns along DP_h. Despite the high computational cost of training, it's infrequent and can be offloaded to an external server for efficient onboard cost prediction. Retraining is only necessary if major road events significantly alter local traffic.

B. *Machine Learning Model*

In this section, the details of the primary families of candidate time-series deep neural network models (LSTM, batched LSTM, and Mix) are explored to assess their suitability for the prediction task.

1) LSTM: The LSTM model is the classical LSTM architecture without batches. LSTM is an artificial recurrent neural network (RNN) architecture extensively used for sequence modeling and prediction tasks. LSTM networks excel at handling problems where inputs possess long-term dependencies or temporal relationships. Traditional RNNs are susceptible to the "vanishing gradient" problem, which impedes their ability to capture extended dependencies in sequences. LSTM networks tackle this challenge by introducing memory cells and gating mechanisms that control the information flow within the network. The key components of an LSTM network are:

- Cell State: It serves as the memory of the network and is responsible for capturing long-term dependencies. The cell state C can selectively forget or store information using gate units.
- Forget Gate: It decides which information in the cell state should be forgotten or discarded. In the time step t, the decision is made using a sigmoid function σ of the current input vector x_t and the current hidden state h_t. The output, called f_t, is a weight value between 0 and 1: 0 means "let nothing through", 1 means "let everything through".
- Input Gate: It determines which information from the input should be stored in the cell state. In the time step t, using always a sigmoid function σ, it is decided which values will be updated (i_t). A tahn layer creates a vector of new candidate values $\tilde{C}_t$ and, combing i_t with $\tilde{C}_t$, an update C_t is created.
- Output Gate: It controls the output of the LSTM unit and determines what information should be output based on the current input and the previous cell state. In time step t, a sigmoid layer decides what parts of the cell state will go to output. This part is called o_t. The output h_t is obtained by multiplying o_t with the cell state C_t transformed by the $tanh$ function. The formulas outlined within it are:

$$f_t = \sigma(W_f(h_{t-1}, x_t) + b_f) \tag{11}$$

$$i_t = \sigma(W_i(h_{t-1}, x_t) + b_i) \tag{12}$$

$$\tilde{C}_t = tanh(W_C(h_{t-1}, x_t) + b_C) \tag{13}$$

$$C_t = f_t C_t + i_t \tilde{C}_t \tag{14}$$

$$o_t = \sigma(W_o(h_{t-1}, x_t) + b_o) \tag{15}$$

$$h_t = o_t tanh(C_t) \tag{16}$$

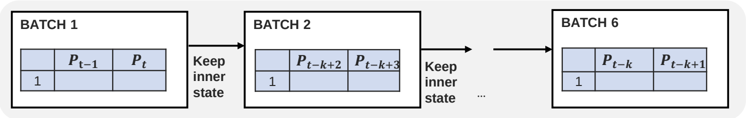


Fig. 3. Structure of batch step

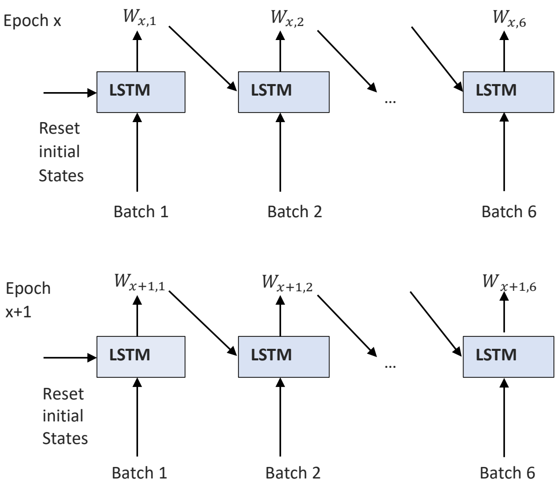


Fig. 4. The structure of a stacked batched LSTM network.

2) Batched LSTM: Batched LSTM is an LSTM model with batches. In LSTM networks, the data is typically processed in batches during training and inference. Let's discuss LSTM with different batches:

- Batch Processing: In LSTM, batch processing refers to dividing the input data into multiple batches. Each batch consists of a subset of the training or test dataset. Batch processing offers several benefits, including improved computational efficiency, parallel processing, and better generalization.
- Variable Batch Sizes: LSTM networks can handle variable batch sizes. It means that each batch can have a different number of sequences or time steps. This flexibility allows for processing sequences of varying lengths within the same batch, which is particularly useful when working with time series data of different lengths.
- Training with Different Batch Sizes: During training, LSTM networks are typically trained on multiple batches, where each batch contains a fixed number of sequences or time steps. The batch size can be chosen based on factors such as computational resources, memory constraints, and the specific characteristics of the dataset. Common batch sizes range from a few samples to several hundreds or even thousands.
- Impact on Training: The choice of batch size can influence the training process. Smaller batch sizes provide more frequent weight updates, which can lead to faster convergence but may result in noisy gradients due to a smaller sample size. Larger batch sizes, on the other hand, offer better gradient estimation but may slow down the training process and require more memory.
- Testing and Inference with Batches: During testing or inference, LSTM networks can process input data in batches as well. This allows for efficient evaluation of multiple samples simultaneously. The batch size for testing can be different from the batch size used during training.
- Handling Remaining Data: When the total number of samples is not divisible by the chosen batch size, there may be a smaller ”remainder” batch at the end of each epoch. Some approaches include discarding the remaining data, padding it to match the batch size, or using dynamic batching techniques that can handle variable batch sizes more gracefully.

Overall, LSTM networks can handle different batch sizes, allowing for efficient processing of time series data in parallel. The choice of batch size depends on various factors, such as computational resources, memory constraints, and the characteristics of the dataset. Careful consideration should be given to selecting an appropriate batch size to balance computational efficiency and model performance. Two types of LSTM with batches exist:

- Stateless batches LSTM: In a stateless LSTM with batches, the internal states of the LSTM cells are reset at the beginning of each batch. This means that the LSTM does not retain any memory of the previous batch when processing the next batch. The LSTM treats each batch as an independent entity.
- Stateful LSTM with batches: In a stateful LSTM with batches, the internal states of the LSTM cells are preserved between batches. The LSTM maintains the hidden states and memory states from the previous batch and uses them as the initial states for processing the next batch. The LSTM carries information from one batch to another within a sequence.

Stateless LSTM with batches is suitable for independent sequences, while stateful LSTM with batches is useful for capturing sequential dependencies and handling variable-length sequences within a batch. For this reason, batched LSTM is a stateful model.

The structure of LSTM with 6 batches is similar to that of LSTM, but the parts of the batches are described in Fig. 3 and 4. While in LSTM in each epoch, only 1 set W is obtained, in batched LSTM in each epoch, 6 sets W are obtained. During each epoch, both LSTM models update their internal parameters (weights and biases) based on the training data and the computed gradients. This parameter update aims to minimize the difference between the model's predictions and the actual targets, effectively improving the model's ability to capture patterns and make accurate predictions. The relationship between different epochs is that each epoch builds upon the progress made by the previous epochs. As the training progresses through multiple epochs, the model's performance typically improves, and the learned representations become more refined. However, it's important to note that the relationship between epochs is not strictly linear or guaranteed to continually improve.

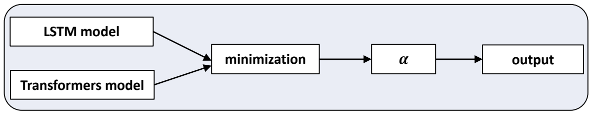


Fig. 5. Structure of mix model.

3) Mixed model: The mixed model, where transformers [24] and LSTMs are run separately, is considered. The key components of a mixed model are:

- Transformer Model: Start by training a transformer model on the time series data. The transformer model captures global dependencies and long-range patterns effectively by utilizing self-attention mechanisms.
- LSTM Model: Train a separate LSTM model on the same time series data. The LSTM model focuses on capturing local dependencies and temporal patterns within the time series.
- Prediction Combination: Once both the transformer and LSTM models are trained, combine their predictions to obtain the final output. This combination is a weighted average, where the weights are calculated to minimize the MSE of the prediction.

Overall, this mixed model combining transformer and LSTM models separately provides a way to leverage the strengths of each architecture and capture both global and local dependencies in the time series. However, it comes with increased complexity and potential challenges in integrating the two models effectively. The structure of the Mix model is described in Fig. 5.

C. Prediction Model Algorithm with Batched LSTM

The algorithm presented is a predictive model that employs a batched LSTM technique to forecast future prices within a time series. Its main goal is to estimate the upcoming price ($\hat{P}_{T_0+1}$), determine the minimum expected price ($\widetilde{p}$) over a specified time interval, and make a decision based on a predefined criterion. To initiate the process, the algorithm takes into account the average prices (X^Z) within a specified time range, namely $[T_0 - Z, T_0 - 1]$. It requires certain parameters, Z, and operates on a model with trainable parameters (θ). The algorithm unfolds in multiple steps. Step 1 represents the initialization and the model training. The algorithm commences by initializing the sequence of average prices (X^Z) and configuring a batched LSTM model with parameters (θ). A crucial step involves defining a batch size, and subsequently, X^Z is reshaped into batches for streamlined processing. The training of the model takes place within a loop, persisting until the successful prediction of $\hat{P}_{T_0+1}$. This training iteration involves updating the LSTM with batches, and the trainable parameters (θ) undergo adjustments as dictated by the model's training procedure. Simultaneously, X^Z is continually updated to incorporate the newly predicted values. The steps from 11 to 18 represent the decision making. Moving forward, the algorithm proceeds to calculate the minimum expected price ($\widetilde{p}$) over the predefined time interval. The decision-making process ensues, determining whether to reserve or wait. This decision hinges on a condition integrating $\widetilde{p}_{S_n}$ and a decreasing function $\epsilon(n)$. The culmination of this phase involves the algorithm providing as output the determined minimum expected price ($\widetilde{p}$) and the corresponding time. Utilizing LSTM for time series prediction ensures the algorithm's ability to capture intricate temporal dependencies. The incorporation of batch processing in the model training phase enhances computational efficiency. Decision making involves a dynamic strategy, employing a threshold ($\epsilon(n)$) and the minimum expected price, guiding the choice between reserving or waiting.

Algorithm 1 Prediction Model Algorithm with Batched LSTM

Input:

- Average prices, X^Z, between time interval $[T_0 - Z, T_0 - 1]$
- Parameters Z
- Model with trainable parameters θ

Output:

- Expected future price, $\widehat{P}_{T_0+1}$, of reserving in the following t
- Minimum expected price, $\widetilde{p}$, for the time interval $[T_0, T_R]$
- Time associated with the lowest price

```
1: procedure PREDICTION MODEL BATCHED LSTM($X^Z, Z, \theta$)
2:     $X^Z \leftarrow [P_{T_0-Z}, P_{T_0-Z+1}, ..., P_{T_0-1}]$
3:     Initialize batched LSTM model with parameters $\theta$
4:     $batch\_size \leftarrow b$                ▷ Set your desired batch size
5:     $X^Z\_batches \leftarrow$ reshape_into_batches($X^Z, batch\_size$)
6:     while $\widehat{P}_{T_0+1}$ not obtained do
7:         for $batch$ in $X^Z\_batches$ do
8:             $\widehat{P}_{T_0+1} \leftarrow$ LSTM_Model($\theta, batch$)
9:             Update $\theta$ using the model's training procedure
10:            $X^Z \leftarrow [P_{T_0-Z+2}, ..., \widehat{P}_{T_0+1}]$
11:        end for
12:    end while
13:    $\widetilde{p} \leftarrow \min(\widehat{P}_{T_0}, \widehat{P}_{T_0+1}, ..., \widehat{P}_{T_R})$
14:    if $\widetilde{p}_{S_n} \leq \widetilde{p} - \varepsilon(n)$ then
15:        $DE \leftarrow$ "reserve"
16:    else
17:        $DE \leftarrow$ "wait"
18:    end if
19:    $\varepsilon(n) \leftarrow \frac{c}{n}$ for $n \in [1, N]$
20:    $\widetilde{p}_{S_n} \leftarrow \min(\widetilde{p}^{S_n}_{T_0}, \widetilde{p}^{S_n}_{T_0+1}, ..., \widetilde{p}^{S_n}_{T_R})$
21:    Return $\widetilde{p}$ and associated time
22: end procedure
```

V. Performance Evaluation

A. Dataset Description

To assess the effectiveness of our methodology, we utilized a historical dataset of Amazon spot prices, which are subject to fluctuations influenced by factors such as capacity, demand, geographic location, and specific instance types [18]. Given the time-sensitive nature of various applications, vehicles require both computing instances and communication links, i.e., bandwidth. Our assumptions are that the pricing for setting up computing and communication resources aligns with the Amazon spot pricing model, as previously referenced in [11],

[9]. For this study, we collected pricing data from all available instances and two specific regions, namely us-west-1b and us-west-1c. This data was collected from April 17, 2021, to May 2, 2021, for training purposes, and from May 3, 2021, to May 8, 2021, for the testing phase of the model.

B. Experimental Results

In this section, the experimental results of the study are presented, encompassing model evaluation and metrics, a comparison of prediction errors among different models, an analysis of the level of risk, and the performance evaluation of cost. The study includes four models: LSTM, batched LSTM, Transformers, and Mix. The experiments were conducted using the PyTorch framework in Python and trained on an NVIDIA GeForce RTX 2080 Ti GPU.

1) Model evaluation and metrics: Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) are three commonly used metrics for evaluating the performance of prediction models and assessing their forecasting accuracy. These metrics provide valuable insights into the effectiveness and reliability of the models in capturing the underlying patterns and making accurate predictions.

Table I presents a comparison of the time consumption among four models, measured in seconds. Batched LSTM and Transformer models demonstrate significantly shorter processing times compared to LSTM and the mix model, thanks to their ability to leverage parallel processing. It is noteworthy that the mix model is the most time-consuming, which is a recognized drawback of this particular approach due to its hybrid nature. Additionally, the table includes a comparison of the time taken for a single forward pass among the three models. Batched LSTM takes advantage of parallel processing by batching sequences together, resulting in improved performance during a forward pass. This parallelization allows for more efficient utilization of hardware resources like GPUs, enabling batched LSTM to achieve faster forward pass times compared to processing each sequence individually, as in LSTM. Transformers are known for their exceptional parallel processing capabilities. By employing self-attention mechanisms, Transformers can simultaneously process all positions in the input sequence, enabling parallelization across different positions. Consequently, Transformers achieve fast forward pass times, especially for long sequences. Interestingly, Transformers and batched LSTM show similar forward pass times, which is advantageous for resource-constrained environments like vehicles, where computational resources are limited and model training need not be performed onboard. The mix model is not considered in this comparison due to its hybrid nature, which makes it challenging to fit into the batch processing paradigm. As a result, the focus is on analyzing the performance of models that fully embrace parallel processing for more efficient and faster computations. In addition, the parameters settings of models are as shown in Table II.

TABLE I. Time Consumption of Training Per Epoch and Per Single Forward Pass Time on the Amazon Spot Pricing Dataset

Training Time per epoch [s]				Time Single Forward-Pass [ms]		
LSTM	Tranf.	Mix	B.LSTM	LSTM	Tranf.	B.LSTM
0.034	0.025	0.188	0.025	2.412	1.889	1.886

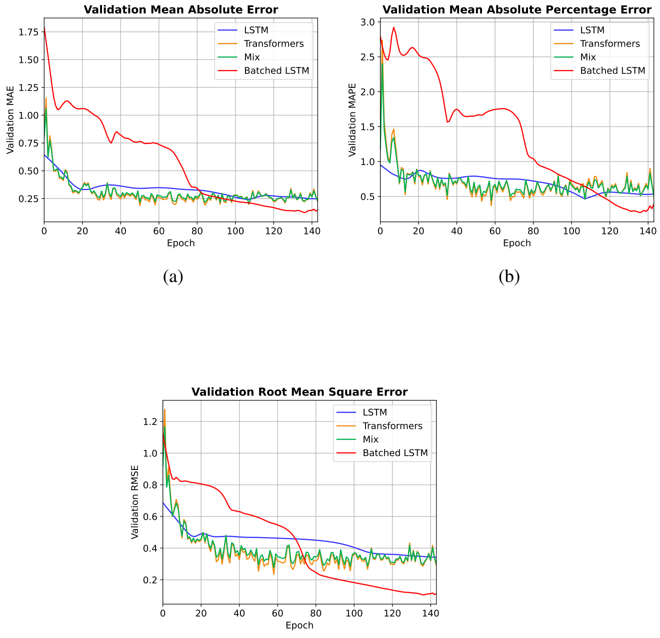
TABLE II. Parameters Settings

Model	Layer	Hidden layers	Dropout percentage
LSTM	1	100	
Transformers	2	10	0.2
Mix model	3	110	0.2
Batched LSTM	1	100	

2) Model prediction error comparison: In this section, the error analysis provides valuable insights into the strengths and weaknesses of each model in capturing different aspects of prediction accuracy. The three error metrics, MAE, MAPE, and RMSE, play distinct roles in assessing prediction accuracy. MAE emphasizes the magnitude of errors; MAPE provides a relative measure of the prediction error as a percentage; and RMSE takes both the magnitude and direction of errors into account, giving more weight to larger errors. The choice of which metric to use depends on the specific context and requirements of the problem at hand. Based on these metrics, the batched LSTM model emerges as the top performer, achieving a lower error rate as demonstrated in Fig. 6. However, for a more comprehensive evaluation, the errors of other models are compared as well. At epoch 140, the Transformers and Mix models show similar errors to the LSTM model when considering MAE and RMSE. On the other hand, taking MAPE into account, the LSTM model exhibits a smaller error compared to Transformers and Mix, though still higher than the Batched model. The lower error rate with MAPE for the LSTM model can be attributed to its effective handling of outliers, as MAPE is less influenced by extreme values compared to RMSE and MAE. Consequently, the LSTM model demonstrates superior robustness in producing predictions when faced with extreme data points.

Fig. 7 clearly shows that the accuracy of the model improves with a longer time interval provided as input. The length of time (in the analyzed case, an hour) that the vehicle has to determine the input's duration directly affects the model's accuracy, with longer input intervals leading to better performance and a lower MAE. Consistently, the LSTM models outperform the Transformer model. They demonstrate better performance in capturing temporal dependencies and patterns in the time series data, consistently yielding lower MAE values compared to the Transformer model across different input matrix lengths. This indicates that the LSTM models are more effective in modeling the sequential nature and capturing relevant information for accurate predictions.

On the other hand, the Transformer model benefits from longer sequences, exhibiting a larger reduction in MAE as the length of the input matrix increases. Although the Transformer model has a higher MAE than the LSTM models at all input lengths, it shows a more significant reduction in MAE with longer sequences. This suggests that the Transformer model can leverage the additional information present in longer sequences to learn more complex patterns. While the MAE remains higher than that of the LSTM models, the relative improvement in performance for the Transformer model is substantial. Based on these observations, it can be concluded that the LSTM models consistently outperform the Transformer model in terms of MAE. The LSTM models'

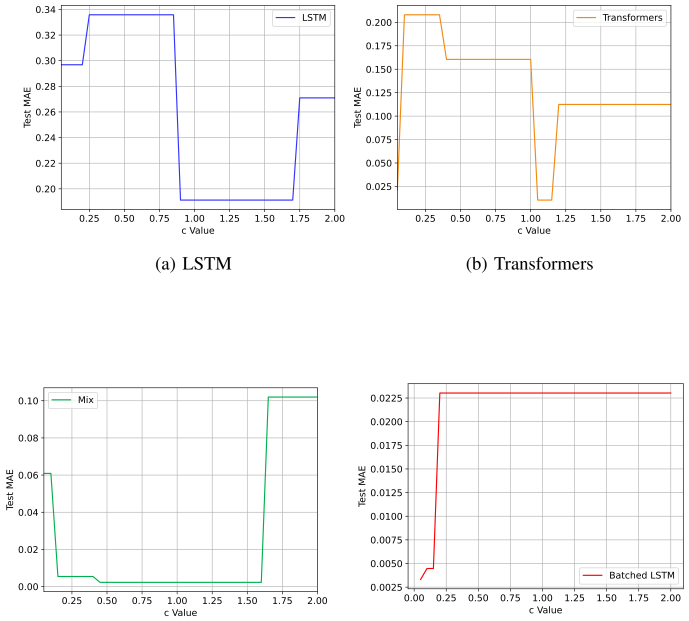


(a)

(b)

(c)

Fig. 6. Prediction errors comparison between models through epochs.



(a) LSTM

(b) Transformers

(c) Mix

(d) Batched LSTM

Fig. 8. Comparison of risk levels among different models.

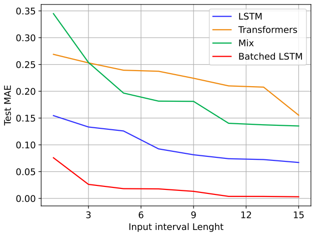


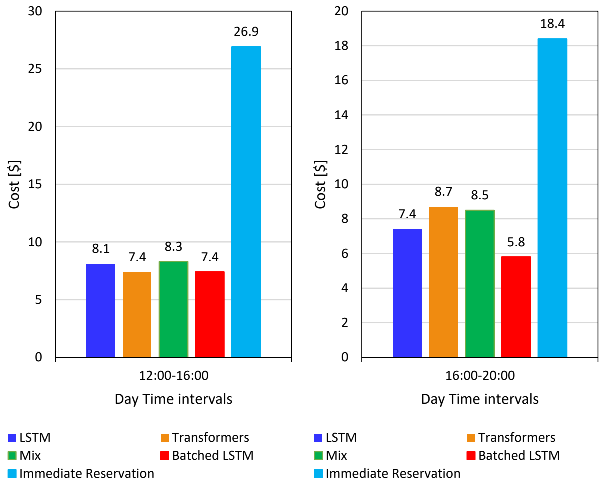
Fig. 7. Input request price time interval.

ability to model sequential dependencies and capture relevant information gives them an advantage over the Transformer model. However, the Transformer model shows promise in handling longer sequences and exhibits a larger reduction in MAE, indicating its potential for capturing more complex patterns and dependencies. In the context of the mix model, if either the transformer or LSTM model poorly estimates the true price, the decision threshold step in the bandwidth cost problem may lead to worse performance of the mix model compared to both the transformer and LSTM models, even if it outperforms them in the estimation step.

Finally, the batched LSTM outperforms the standard LSTM due to its consideration of batches, enabling it to produce more generalized results. LSTM models trained with batches tend to exhibit improved generalization performance. By exposing the model to multiple sequences within each batch, it gains exposure to a diverse range of patterns and can capture broader temporal dependencies. This increased variety of examples enhances the model's ability to make predictions on unseen data, resulting in improved generalization and more accurate forecasts, even with shorter input to the model. As observed in Fig. 7, the vehicle only needs a small number of hours (i.e., 1-3 hours) as input to the model to achieve better and more accurate predictions of bandwidth cost. This indicates that the model's performance remains consistent even with limited input, closely resembling real-world scenarios. The advantage of using a shorter input interval is that the vehicle does not need to wait for an extended period to find the best price for bandwidth.

3) Level of risk analysis: The analysis of risk levels among different models sheds light on their precision and helps identify the best c values for optimizing prediction accuracy. When comparing the optimal value of risk achieved by various models in Fig. 8, the batched LSTM demonstrates the lowest value of c, indicating higher precision, while Transformers exhibit the highest value of c. It's important to note that as c increases, precision decreases. For instance, when $\tilde{p}^{S_n} = 1$ and $\tilde{p}$ equals 1.1, the algorithm reserves with a c of 0, whereas a c of 0.2 would prompt the algorithm to wait wrongly. Consequently, batched LSTM, being the most precise algorithm, has the lowest MAE associated with the smallest c, and the change in MAE associated with varying c is minimal. However, all the best c are very small.

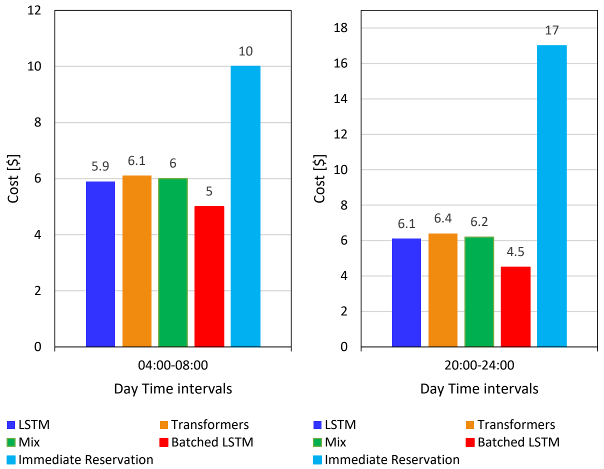
4) Cost performance: In this subsection, a comprehensive evaluation of the cost performance of the prediction models is conducted by comparing them with the benchmark immediate reservation request scheme. Three distinct benchmark scenarios are explored, each characterized by different time intervals during which the vehicle searches for the most cost-effective option. As mentioned earlier, the time interval represents the desired departure time for the vehicle. Furthermore, time steps are utilized to divide the aforementioned time interval into smaller segments, such as hours or half-hours.



(a)

(b)

Fig. 9. Comparison of cost performance across benchmark with time intervals $[T_0\ , T_R\ ] = 4$ hr and time steps $\delta t = 1$ hr.



(a)

(b)

Fig. 10. Comparison of cost performance across benchmark with time intervals $[T_0\ , T_R\ ] = 4$ hr and time steps $\delta t = 0.5$ hr.

Subsequently, the total cost is calculated by determining the number of BSs that the vehicle reserves along its driving path to reach the final destination. The calculation enables an effective assessment of the performance of prediction models in comparison to the established benchmark. The analysis of cost performance highlights the effectiveness of the proposed method in securing reservations at lower prices. Fig. 9 and Fig. 10 illustrate the comparison between the costs of various approaches and immediate reservations. In all cases, the prediction methods derived from the different approaches outperform the immediate reservation scheme in obtaining a better price. This is due to the fact that the proposed approach identifies the optimal price, which may differ significantly from the immediate reservation price.

Among the estimation methods, batched LSTM exhibits the smallest Mean Absolute Error (MAE), resulting in an estimated value that closely approximates the true best price, deviating distinctly from the immediate price. Nevertheless, all four estimation methods capture this difference, making the proposed method valuable for securing reservations at lower prices.

Comparing Fig. 9 with Fig. 10, it is evident that as the time steps (δt) increase from 0.5 hr to 1 hr, the price of immediate reservations may rise, while the cost savings from employing the proposed approach increase. For example, comparing the savings obtained using the estimated price from batched LSTM with the immediate reservation for the interval 12.00-16.00, the saving is 72.49% for 1 hr (Fig. 9.a) and time interval 20.00-24.00 for 0.5 hr (Fig. 10.b) is 73.52%.

VI. Conclusions

In conclusion, this research effectively addresses the challenges in decision time for bandwidth reservation, particularly within the context of safety-critical vehicular applications. The paper introduces an optimized approach using batched LSTM to predict bandwidth costs within a short duration. By organizing data into batches during the training phase, the model enhances both computational efficiency and prediction accuracy. This approach has proven highly effective, through the utilization of real price data, resulting in significant cost reductions by 27% compared to traditional time-series machine learning models, as we have provided in the experimental results. In future work, we aim to explore dynamic BS ranges and varying MNO numbers for more realistic and intelligent reservation request strategies.

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An Algorithm Based on Priority Rules for Solving a Multi-drone Routing Problem in Hazardous Waste Collection

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***Abstract*—This research investigates the problem of assigning pre-scheduled trips to multiple drones to collect hazardous waste from different sites in the minimum time. Each drone is subject to essential restrictions: maximum flying capacity and recharge operation. The goal is to assign the trips to the drones so that the waste is collected in the minimum time. This is done if the total flying time is equally distributed among the drones. An algorithm was developed to solve the problem. The algorithm is based on two main ideas: sort the trips according to a given priority rule and assign the current trip to the first available drone. Three different priority rules have been tested: Shortest Flying Time, Longest Flying Time, and Median Flying Time. Two recharging conditions are maintained: recharging needed time and recharging full duration. By applying each priority rule and each recharging condition, we generate a six versions of the algorithm. The six versions of the proposed algorithm were implemented in Java programming language.The results were analyzed and compared proving that the Longest Flying Time priority rule surpasses the other two rules. Moreover, recharging a drone just enough for taking the next trip proved to be better than fully recharging it.**

***Keywords*—Drones; trip assignment; priority rules; flying capacity; load balance**

I. Introduction

The Vehicle Routing Problem (VRP) is an important problem discussing the process of finding the optimal routes for a single or multiple vehicles, to perform a certain task or service. VRPs have been extended for numerous of problems. Most recently, VRPs using a single or multiple drones also called Unmanned Aerial Vehicles (UAVs) have spread widely. Those varied to truck-drone, truck-multi-drone, and multi-truck-multi-drone problems to achieve precise goals and maintaining a set of constraints. The author in [1] presented the vehicle routing problem with drones (VRPD) as a design of the combination of truck-drone routes and timetables to serve a group of customers with specific requirements and time limitations. The applications of VRPD or as called, Drone Routing Problems (DRPs) received a massive amount of attention from different fields and concerned parties. Media has shown interest in drones equipped with cameras to cover stories in different areas [2], commerce companies have been intrigued with last-Mile delivery using UAVs for speeding the process and lowering shipping costs [3], scientists for great discoveries [4], medical staff for urgent transportation of equipment [5], program developers and even the entertainment sector for mesmerizing drones shows. Environmentalists have utilized drones for addressing great problems threatening our earth, affecting humans and all living creatures [6]. Specialized VRPs regarding critical environmental issues such as CO2e emission, air pollution and global warming are called Green Vehicle Routing Problems (G-VRPs). Hazardous waste is another serious problem that puts us in danger by the minute. Taking advantage of the VRPD and G-VRP, our study highlights the formation of a hazardous waste collection plan, where waste is collected in the minimum time possible using multiple drones (MTMD). The authors in [7] proved the strongly NP-hardness of the problem and proposed a 2-phase approach and a linear program to solve it using a single Unmanned Aerial Vehicle. In their research, a set of efficient trips have been produced for each solved instance. Each trip is a path that starts from a depot site, visits some other sites to collect the maximum waste in the minimum time, respecting the drone flying and waste capacities before returning back to the depot for charging and some minor maintenance. In the current research, we adopt those datasets of generated trips and extend the study using multiple drones. The motivation behind this research was mainly to propose efficient algorithms that will allow an optimal or near-optimal use of the flying and weight capacities of a fleet of drones in order to collect hazardous waste in a shortest time from many sites. This research studies a new Drone Routing Problem (DRP) using m drones. Constraints related to the flying capacity and recharge duration of each drone are set. The aim of the study is to assign pre-generated tours in [7] so that completion time of the last drone is minimum. To solve this problem, the authors proposed priority rules-based algorithm. These rules have the purpose of sorting the trips prior distribution among the drones. The algorithm allows a maximum use of each drone's charge without exceeding the flying capacity. An experimental study using benchmarks was conducted to compare the efficiency of the proposed algorithm for each priority rule.

The remaining of the paper is structured as follows. In Section II, the literature review highlights the related and relevant areas of the research. The methodology used for conducting the research is detailed in Section III. Next, the experimental results and discussion are explained in Section IV followed by the conclusion and future work.

II. Literature Review

New Vehicle Routing Problems (VRPs) studies have been intensively emerging in the last few decades, especially those using Unmanned Aerial Vehicles (UAVs). The author in [8] acknowledged that the interest in the use of drones in various applications has grown significantly in recent years. Accompanied with specific constraints, limitations and several goals, VRPs are becoming progressively challenging. Most commonly, Different approaches to solve Drone Routing Problems (DRPs) have been proposed for last-Mile delivery. Moreover, transportation of medical equipment as in [9], collection of waste, surveillance, search and rescue missions and even forest monitoring to detect fire as presented in [10]. The author in [11] stated that similar to the traditional vehicle routing problem, the vehicle routing problem with drones (VRPD) involves the use of drones in addition to trucks for delivery. When trucks and drones are routed together, the challenge is substantially more complex and distinct from traditional vehicle routing problems.

Most DRPs were organized to truck-drone routing problems, as [12] demonstrated how incorporating truck-drone tandems into transportation systems can enhance delivery speed while also allowing the fleet size to be reduced without impacting delivery times or adding to truck drivers' workload. The author in [13] presented and solved a truck-drone hybrid routing problem with time-dependent road travel time (TDHRP-TDRTT) to resolve the truck-drone cooperative issue. TDHRP-TDRTT was solved using an iterative local search heuristic method. Whereas, in [14], they thought of several drones, each with a different set of capabilities, such as speed and battery life, are transported by and sent out from the truck, working together to satisfy customers. The truck must wait until each drone returns and numerous drones can all be dispatched at once. The proposed model was given the name heterogeneous drone-truck routing problem (HDTRP), and a formulation of the problem using mixed-integer programming was provided.

Likewise, A parallel Drone Scheduling Traveling Salesman Problem was solved in [15]. In this approach, deliveries are divided between a truck and one or more drones. The truck goes on a tour from the depot, but the drones can only go back and forth. The goal is to finish as soon as possible. The problem was expanded by taking into account many vehicles. A hybrid metaheuristic, as well as a Mixed Integer Linear Programming formulation and a simple branch-and-cut algorithm, were also presented as solutions. In addition, A mixed-integer linear programming (MILP) model for the multi-trip Capacitated Arc Routing Problem was proposed in [16] to reduce the overall cost of waste collection (CARP).

Logically, the algorithms developed in solving the problems varied. A widely known algorithm is the neighborhood search. In [17], an Adaptive Large Neighborhood Search metaheuristic for the vehicle routing problem with drones (VRPD) was proposed, following minimum time and cost constraints, using multiple trucks. They developed a mathematical model to create a problem close to the Flying Sidekick Traveling Salesman Problem to optimize huge instances. Nevertheless, a tabu search heuristic algorithm in [18] proposed a new neighborhood generation process for a distribution company, to transport commodities from a single depot to multiple dealers. And a hybrid genetic algorithm was studied in [19] combining sweep and genetic algorithms in an enhanced approach. Both are recognized algorithms to solve the VRPD in the literature.

Other important algorithms are those whose called nature based. An ant colony optimization (ACO) technique was developed to solve the NP-hard VRPs with drones in [20]. The studies showed that the suggested ACO algorithm can solve the VRDP efficiently for diverse size instances and area distributions. Similarly, a novel dynamical artificial bee colony (DABC) was used in [21] to reduce operating costs. To identify employed bee swarm and onlooker bee swarm, two bee swarms were formed. Also, variable neighborhood descent was used in employed bee phase and onlooker bee phase in varying methods. An artificial bee colony-based hybrid approach was developed to solve the waste collecting problem while taking the halfway disposal pattern into account in [22]. Moreover, [23] suggested a Particle Swarm Optimization (PSO) algorithm to solve uncertain VRP, alongside a decoding scheme to improve its efficiency. According to [24], a simulated annealing heuristic algorithm was proposed to solve one of the Green Vehicle Routing Problems (G-VRPs), which is the Hybrid Vehicle Routing Problem (HVRP).

The clustering algorithms are majorly common. The author in [25] proposed two different hybrid metaheuristic algorithms in regards of the Clustered Vehicle Routing Problem (Clu-VRP). The first algorithm relies on an Iterated Local Search algorithm, in which only possible solutions are searched. The second one is a hybrid genetic search where the shortest Hamiltonian path between every set of vertices inside each cluster is precomputed.

The Location-Routing Problem for delivering orders to a group of clients was discussed in [26]. They attempted to reduce the overall CO_2 emissions using trucks and drones for last-mile deliveries. The problem was resolved using a mathematical model. Their findings focused on how adopting greener transportation technology can be a start to the substantial contribution that UAVs make to problems with parcel delivery routing. Hence, it is considered one of the G-VRPs, which highlight serious environmental issues like high CO_{2e} emission, pollution, global warming, low sustainability lifestyle and many others, as clearly stated in [27]. Waste collection problem is another example of the G-VRPs. Conveniently, [28] introduced a particle swarm optimization (PSO) approach in a capacitated vehicle-routing problem (CVRP) model to establish the optimal waste collection and route optimization solutions. The PSO-based CVRP model included threshold waste level (TWL) and scheduling approaches. Solomon's insertion algorithm was developed to solve a real-world waste collection vehicle routing problem with time windows (VRPTW) in [29].

This research investigates the process of collecting hazardous waste from different sites using constrained drones (UAVs), proposing priority rules-based algorithm to help efficiently collect the waste in the minimum time using multiple drones (MTMD). Using the outcomes of [7] as the base of the study, extending it by assigning the trips to multiple drones instead of a single drone.

Despite the magnitude of research conducted on VRPs following versatile approaches and proposing applicable solutions, shedding lights on such problem with this significance and effect on the daily life and unknown future of livings on the face of earth is crucial and deserving. Also, employing the latest modern technology like drones to accomplish the desired goal efficiently makes a distinctive difference. On that account, presenting an algorithm maintaining sensitive constraints and imposing priority rules as a solution would narrow the gap and expedite the plan to a safer, healthier and waste free planet.

To the best of our knowledge, there is no existing literature that addresses the specific challenges associated with using drones in hazardous waste collection. Therefore, we are unable to compare the proposed algorithm with existing solutions in this context.

III. Research Methodology

To assign the trips to the drones in an efficient way so that the total waste will be collected from all sites in the minimum time, we developed an algorithm that is mainly based on three principles:

- Order the trips to be traveled according to their flying times. The trips are then executed according to either an increasing order of their flying times: Shortest Flying Time (SFT), a decreasing order of their flying times: Longest Flying Time (LFT), or alternatively from the median time: Median Flying Time (MFT).
- Assign the current trip to the first available drone. This principle will guarantee an efficient use of the drones, balance distributing the flying times between the drones, and collect the waste in a minimum time.
- When the current charge of a given drone is less than the flying duration of the next trip, then charge it according to two principles. The first is fully recharge the drone before taking the next trip. The second is to recharge the drone just enough for it to take the next trip.

The suggested algorithm enables multiple drones to access the list of trips at the same time, where each drone has a maximum flying and weight capacity, as well as a recharging duration. The flying capacity and drone's recharge are the two key constraints defined. The algorithm's two primary tasks are: parallel assignment of trips to multiple drones and recharging of drones. The trips are assigned to the drones as long as the list of trips is not empty, employing one of three proposed priority rules and following one of the charging principles. As a result, six versions of the main algorithm are proposed. The details of these algorithms are illustrated in Algorithms 1 to 4. Note that Algorithms 1 and 2 each has two versions. A version uses the SFT rule and another version uses the LFT rule. The notations used to develop the algorithm are summarized in Table I.

TABLE I. Problem Notations

n	Number of trips in an instance
m	Number of drones
T	Maximum flying time of a drone if fully charged
r	Time needed to fully recharge a drone
c_j	Completion time of the last trip assigned to drone $j, 1 \leq j \leq m$
t_i	Flying duration of trip $i, 1 \leq i \leq n$
q_j	Remaining flying capacity of drone j

Algorithm 1 Assignment of trips to drones using SFT/LFT rule and charging drones when needed

```
 1: input: $m, n, T, r, t_i$
    output: $C_{max}$: The completion time of the last trip.
 2: Sort $t_i$ in increasing/decreasing order
 3: for $j \leftarrow 0$ to $m - 1$ do
 4:     $c_j \leftarrow 0$
 5:     $q_j \leftarrow T$
 6: end for
 7: $i \leftarrow 0$
 8: while $(i < n)$ do
 9:     $a \leftarrow\ index\ of \min c_j$
10:     if $(q_a < t_i)$ then
11:         $c_a \leftarrow \frac{t_i - q_a}{T} \times r + t_i$
12:         $q_a \leftarrow 0$
13:     else
14:         $c_a \leftarrow c_a + t_i$
15:         $q_a \leftarrow q_a - t_i$
16:     end if
17:     $i \leftarrow i + 1$
18: end while
19: return $\max c_j$
```

Algorithm 2 Assignment of trips to drones using SFT/LFT rule and charging drones fully

```
 1: input: $m, n, T, r, t_i$
    output: $C_{max}$: The completion time of the last trip.
 2: Sort $t_i$ in increasing/decreasing order
 3: for $j \leftarrow 0$ to $m - 1$ do
 4:     $c_j \leftarrow 0$
 5:     $q_j \leftarrow T$
 6: end for
 7: $i \leftarrow 0$
 8: while $(i < n)$ do
 9:     $a \leftarrow index\ of\ \min c_j$
10:     if $(q_a < t_i)$ then
11:         $c_a \leftarrow \frac{T - q_a}{T} \times r + t_i$
12:     else
13:         $c_a \leftarrow c_a + t_i$
14:     end if
15:     $q_a \leftarrow q_a - t_i$
16:     $i \leftarrow i + 1$
17: end while
18: return $\max c_j$
```

Note that steps 3 to 5 in all algorithms have the purpose of initializing the completion times of the drones to zeros and set their initial charge to full so that they can fly for T unites of time. Step 9 assigns the next trip to the first free drone. Step 10 in Algorithms 1 and 2 and 17 in Algorithms 3 and 4 means that the drone does not have enough charge to fly the next trip. For that reason, the drone needs either to be partially enough charged to fly the next trip (as in algorithms 1 and 3) or fully charged up to its maximum flying capacity T (as in algorithms 2 and 4). The last statement in all algorithms returns the maximum completion flying time of the last trip for all drones. The six proposed algorithms ensure an early completion time of the waste collection by assigning the next trip to the first available drone. This method maintains also an equilibrium between the total flying time between the drones.

Algorithm 3 Assignment of trips to drones using MFT rule and charging drones when needed

```
input: $m, n, T, r, t_i$
output: $C_{max}$: The completion time of the last trip.
Sort $t_i$ in increasing order
for $j \leftarrow 0$ to $m-1$ do
    $c_j \leftarrow 0$
    $q_j \leftarrow T$
end for
$left \leftarrow \lfloor \frac{n}{2} \rfloor,\ right \leftarrow \lfloor \frac{n}{2} \rfloor + 1,\ k \leftarrow 0$
while ($k < n$) do
    $a \leftarrow index\ of\ \min c_j$
    if ($k \mod 2 = 0$) then
        $i \leftarrow left$
        $left \leftarrow left - 1$
    else
        $i \leftarrow right$
        $right \leftarrow right + 1$
    end if
    if ($q_a < t_i$) then
        $c_a \leftarrow \frac{t_i - q_a}{T} \times r + t_i$
        $q_a \leftarrow 0$
    else
        $c_a \leftarrow c_a + t_i$
        $q_a \leftarrow q_a - t_i$
    end if
    $k \leftarrow k + 1$
end while
return $\max c_j$
```

Algorithm 4 Assignment of trips to drones using MFT rule and and charging drones fully

```
input: $m, n, T, r, t_i$
output: $C_{max}$: The completion time of the last trip.
Sort $t_i$ in increasing order
for $j \leftarrow 0$ to $m-1$ do
    $c_j \leftarrow 0$
    $q_j \leftarrow T$
end for
$left \leftarrow \lfloor \frac{n}{2} \rfloor,\ right \leftarrow \lfloor \frac{n}{2} \rfloor + 1,\ k \leftarrow 0$
while ($k < n$) do
    $a \leftarrow index\ of\ \min c_j$
    if ($k \mod 2 = 0$) then
        $i \leftarrow left$
        $left \leftarrow left - 1$
    else
        $i \leftarrow right$
        $right \leftarrow right + 1$
    end if
    if ($q_a < t_i$) then
        $c_a \leftarrow \frac{T - q_a}{T} \times r + t_i$
    else
        $c_a \leftarrow c_a + t_i$
    end if
    $q_a \leftarrow q_a - t_i$
    $k \leftarrow k + 1$
end while
return $\max c_j$
```

IV. Experimental Study

The six versions of the proposed algorithms were implemented in Java. Distributing the number of trips among multiple drones grants completing all the trips in a sooner time than assigning all the trips to a single drone, because all the drones are flying simultaneously; whenever a drone completes a trip and it is available in the depot, the program assigns another trip to it, not taking into account the status of the other drones.

Testing the program using the three priority rules: SFT, LFT and MFT while recharging only for the time needed once, and again recharging the drones till they are full, generated six distinctive cases. Twenty instances varying from 101 to 941 sites, with a number of trips in the range $[23, 249]$, have been used for validation of the proposed algorithms. A summary of results is shown in Tables II, III, IV, and V. For the six algorithms, the time each drone takes to complete the trips assigned to it was compared; the longest time means that it is the last drone to finish. As observed, the last drone finishing time of the cases that follow the LFT rule and recharge only for the time needed, is mostly the shortest, which means the LFT rule frequently guarantees a faster execution of the routing process. However, in some cases, multiple drones finish on the same time.

TABLE II. Values of C_{max} for Different Instances when $m = 2$

		Needed charge			**Full charge**		
Instance	n	SFT	LFT	MFT	SFT	LFT	MFT
I_{101}	23	294	289	**284**	296	293	**284**
I_{121}	28	392	**384**	392	393	388	393
I_{141}	32	416	**409**	416	416	411	416
I_{161}	34	353	**345**	353	353	349	353
I_{181}	52	606	**598**	606	607	600	607
I_{341}	69	725	**719**	720	725	720	720
I_{301}	75	708	702	**699**	708	703	703
I_{381}	82	960	**952**	960	960	957	957
I_{321}	87	1107	**1101**	1097	1076	1089	1098
I_{361}	100	866	**862**	866	866	**862**	866
I_{461}	118	1365	**1357**	1365	1365	**1357**	1365
I_{481}	127	**960**	1128	1133	1365	1357	1133
I_{641}	121	1494	**1470**	1488	1494	1471	1488
I_{661}	143	1847	**1840**	**1840**	1847	1841	1841
I_{701}	156	1519	**1511**	1519	1519	1512	1519
I_{721}	162	1662	**1652**	1662	1662	1658	1662
I_{741}	183	1493	**1487**	1489	1493	1488	1489
I_{861}	194	2188	**2182**	2188	2188	2184	2188
I_{901}	207	2158	**2151**	2153	2158	2152	2153
I_{941}	249	2159	**2151**	2154	2159	2152	2154

Moreover, the three cases where the drones are fully recharged every time the battery ran out, took a slightly longer total time to complete all the trips, regardless of the number of drones used, than those three cases which the drones are recharged for only the time needed to be assigned the next suitable trip. Table VI confirms this result for instance I_{101}.

Although, the recharge count could be the same for both recharging conditions, the remaining charge in the cases that recharge only the needed duration is always zero. Whereas the cases that recharge fully, have useless remaining charge; that adds extra period of time, which increases the completion time of all the trips. Therefore, it is better to consider the cases that will reduce the total time by charging the drones only for the time needed.

TABLE III. VALUES OF C_{max} FOR DIFFERENT INSTANCES WHEN $m = 3$

		Needed charge			Full charge		
Instance	n	SFT	LFT	MFT	SFT	LFT	MFT
I_{101}	23	196	**191**	195	198	195	197
I_{121}	28	272	266	**264**	273	270	**264**
I_{141}	32	284	**277**	283	284	279	284
I_{161}	34	246	**234**	242	246	237	242
I_{181}	52	419	**403**	408	420	408	410
I_{341}	69	483	**474**	484	483	476	485
I_{301}	75	467	**462**	471	470	465	469
I_{381}	82	651	**640**	647	651	642	646
I_{321}	87	729	**726**	735	730	729	736
I_{361}	100	591	**581**	584	591	582	584
I_{461}	118	923	**911**	921	923	**911**	918
I_{481}	127	767	**752**	761	767	754	762
I_{641}	121	1004	**995**	1000	1004	**995**	1000
I_{661}	143	1227	**1226**	1230	1233	1229	1232
I_{701}	156	1015	**1007**	1018	1015	**1007**	1020
I_{721}	162	1112	**1098**	1114	1112	1102	1113
I_{741}	183	997	**987**	1000	997	988	1000
I_{861}	194	1465	**1457**	1466	1464	1458	1465
I_{901}	207	1437	**1430**	1443	1438	1431	1442
I_{941}	249	1444	**1431**	1445	1444	1431	1444

TABLE IV. VALUES OF C_{max} FOR DIFFERENT INSTANCES WHEN $m = 4$

		Needed charge			Full charge		
Instance	n	SFT	LFT	MFT	SFT	LFT	MFT
I_{101}	23	148	**142**	150	150	143	151
I_{121}	28	200	**190**	201	200	193	201
I_{141}	32	212	**203**	215	212	205	215
I_{161}	34	191	**173**	186	191	181	185
I_{181}	52	309	**301**	312	309	305	313
I_{341}	69	373	**363**	368	373	366	368
I_{301}	75	352	**346**	352	356	349	361
I_{381}	82	488	**480**	486	488	482	487
I_{321}	87	554	**548**	554	555	551	555
I_{361}	100	440	**431**	444	441	432	444
I_{461}	118	692	**681**	691	692	682	692
I_{481}	127	578	**562**	577	578	564	577
I_{641}	121	761	**749**	755	761	**749**	755
I_{661}	143	925	**919**	928	927	920	928
I_{701}	156	765	**754**	767	766	756	768
I_{721}	162	838	**827**	841	838	832	842
I_{741}	183	748	**742**	755	748	744	754
I_{861}	194	1103	**1095**	1102	1104	1098	1102
I_{901}	207	1085	**1075**	1085	1085	**1075**	1085
I_{941}	249	1091	**1079**	1087	1091	1083	1088

TABLE V. VALUES OF C_{max} FOR DIFFERENT INSTANCES WHEN $m = 5$

		Needed charge			Full charge		
Instance	n	SFT	LFT	MFT	SFT	LFT	MFT
I_{101}	23	125	**114**	125	126	118	126
I_{121}	28	169	**159**	167	169	162	167
I_{141}	32	181	**170**	176	181	172	176
I_{161}	34	155	**135**	155	155	136	154
I_{181}	52	261	**242**	257	262	247	258
I_{341}	69	294	**286**	299	294	287	299
I_{301}	75	281	**274**	287	284	278	292
I_{381}	82	398	**384**	394	398	390	399
I_{321}	87	451	**444**	450	452	447	452
I_{361}	100	355	**345**	360	355	**345**	360
I_{461}	118	556	**543**	556	557	546	557
I_{481}	127	471	**453**	468	471	455	467
I_{641}	121	613	**602**	609	613	**602**	609
I_{661}	143	750	**738**	750	750	739	749
I_{701}	156	620	**610**	619	620	613	619
I_{721}	162	676	**662**	673	676	663	671
I_{741}	183	603	**595**	605	603	596	604
I_{861}	194	883	**872**	885	883	876	883
I_{901}	207	876	**865**	872	876	866	872
I_{941}	249	876	**860**	877	874	**860**	876

TABLE VI. TOTAL TIME COMPARISON FOR INSTANCE I_{101}

	Needed charge			Full charge		
m	SFT	LFT	MFT	SFT	LFT	MFT
2	562	563	562	566	569	568
3	556	557	556	561	566	559
4	549	550	550	557	557	556
5	544	543	544	553	558	553

In addition, the average of the time each drone took to complete the assigned trips was calculated. The difference between the time each drone took, and the average was also calculated, to illustrate how balanced the assigning of trips among the drones was. The total difference of those differences was then summed up to accentuate the exact gap between the time all the drones took to complete the trips and the average of it. It is noticeable that the total difference generated by SFT rule is always the biggest compared to the LFT and MFT rules. Whilst, the MFT cases often have smaller total difference than the SFT cases and a few of them have the same total difference as the LFT or SFT cases. In numerous instances, the MFT cases have the smallest total difference out of all three rules. Furthermore, a decreasing pattern in the number of those instances was noticeable, where the number of instances and the number of drones used have an inverse relationship; whenever the number of drones used increases, the number of the instances having the smallest total difference in the MFT cases decreases. However, the LFT cases mostly have the smallest total difference amongst all three. Additionally, in some LFT cases the total time of all the drones is the same as the average time, which means the total difference is zero. This comparison truly demonstrated how the LFT rule performs best in regards of the assignment of trips among the drones, despite their number, which ensures that all the drones take up nearly the same time to complete the trips. Moreover, it is an indication that the drones visit approximately the same number of trips. As a resultant, sorting the trips from the longest flying time to the shortest flying time (LFT) almost equally assigns the trips to the drones, which executes a more efficient program, effectively fulfilling the objective of the proposed algorithm MTMD.

"Fig. 1, "Fig. 2", "Fig. 3" and "Fig. 4" below, clarify the contrast between the total differences in each rule (SFT, LFT and MFT) for all 20 instances using 2, 3, 4 and 5 drones.

V. CONCLUSION AND FUTURE WORK

A. Conclusion

In conclusion, studying the Vehicle Routing Problem using Drones (VRPD) and how it can be applied to help finding a solution to the accumulated hazardous waste problem was the first step. The diversified literature of VRPs gave the proper background and knowledge to investigate this major problem and propose an algorithm to resolve it.

Adopting the outcomes of an existent research as a dataset, six versions of a proposed algorithm were brought forward that allow multiple drones to access the list of trips at the same time, where the drones have maximum flying and weight capacities and a recharge duration. Concentrating on the flying capacity and the recharging of drones as constraints, the

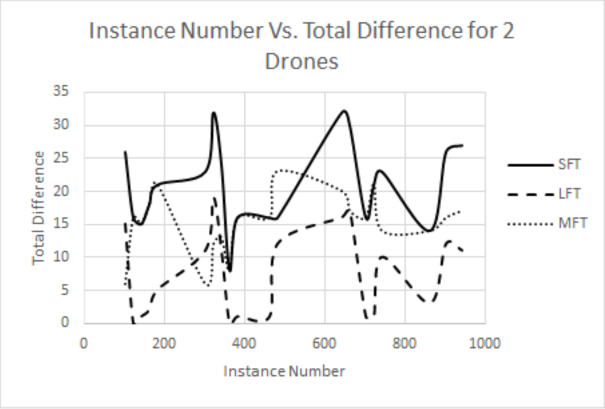

Fig. 1. Total differences for each rule using 2 drones.

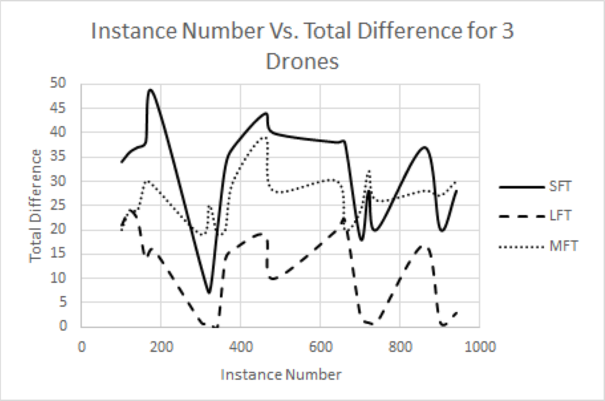

Fig. 2. Total differences for each rule using 3 drones.

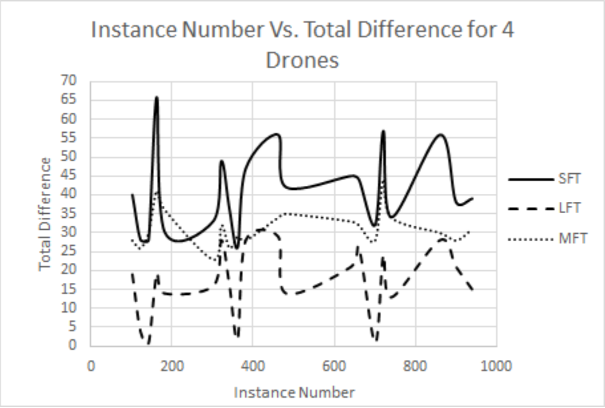

Fig. 3. Total differences for each rule using 4 drones.

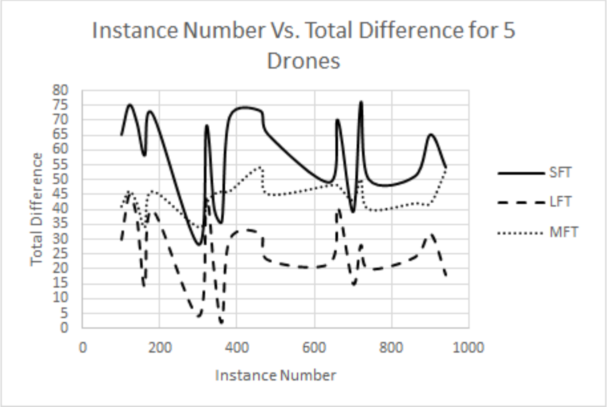

Fig. 4. Total differences for each rule using 5 drones.

presented algorithms handle the routing through two main tasks: the assignment of trips to multiple drones and recharging of drones. It suggested three priority rules in sorting the flying times before assigning them to the drones. The first rule is sorting from the shortest to the longest flying time (SFT) in ascending order. The second rule is sorting from the longest to the shortest flying time (LFT) in descending order. The third rule is sorting the flying times in ascending or descending order first and then starting from the median trip time (MFT). Following each rule, whenever the drones need recharging, two conditions were taken into consideration: recharging the drones just for the time needed to be assigned the next adequate trip or recharging the drones fully, taking their total recharge duration. Hence, the algorithms map routes in minimum time using multiple drones (MTMD).

Moreover, the algorithm's versions were implemented using Java to program was developed validating the algorithm, which produced six cases that test each individual rule (SFT, LFT and MFT) with both recharging conditions (needed and full).

After various testing of the six cases, the output of the program resulted in valuable findings. The LFT rule was proven the current best in assignment of trips to the multiple drones. It almost distributes the trips equally, which means approximately the same total flying time, recharge count and trip count of the drones. The program was tested using common several testing types as well, to assure its effectiveness in following the MTMD algorithm.

B. Future Work

Aggregating the work done, positive improvements are expected to better the research, starting from developing a program with higher performance and dedicating enough time to test all the instances of the dataset using a greater number of drones.

In addition, the Drone Routing Problem (DRP) is progressing continuously; researchers are studying new challenging extensions of it momentarily. Consequently, proposing a better algorithm to develop an enhanced program as a solution to this substantial problem is an aspiration kept in mind. An existing similar problem called the Subset-Sum problem could be beneficial for evolving the rules the MTMD algorithm proposed.

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The Management System of IoT Informatization Training Room Based on Improved YOLOV4 Detection and Recognition Algorithm

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Abstract—**In response to the problems of low recognition rate and long system operation time in equipment detection management in the existing IoT information training room management system. A research has proposed an IoT information training room equipment detection management system on the ground of an improved YOLOV4 detection and recognition algorithm to solve the above problems. Firstly, it used the YOLOV algorithm to detect and identify equipment in the IoT information training room. Then, it used clustering methods to improve the YOLOV algorithm, thereby enhancing the detection accuracy and robustness of the algorithm, and thereby enhancing the performance of the equipment management system in the equipment management process of the training room. Finally, performance validation of the training room management system was conducted using datasets and simulation experiments. The results showed that the loss value of the training room equipment management system constructed using the improved YOLOv4 algorithm during the training process was 0.16. The accuracy and recall rates of device recognition were 95.71% and 92.83%, respectively. And the detection false alarm rate during the device detection and recognition process was only 2.15%, with a mAP value of 91.66%, and the detection and recognition indicators are higher than those of the comparison method. This indicates that the training room equipment management system constructed in the study has good adaptability in equipment detection and recognition in IoT information training rooms. The research aims to provide effective technical support for the management system of IoT training room equipment.**

Keywords—YOLOV4 algorithm; Internet of Things informatization; training room; management system; detection and recognition

I. Introduction

As the boost of Internet of Things (IoT) technology, IoT information training rooms, as a new type of teaching and practical environment, are widely used in various universities. Çobanoğlu et al. investigated the laboratory operation needs of K-12 teachers and students using a survey method [1]. Automated detection and identification of equipment can improve the efficiency and accuracy of equipment management, Kan et al. conducted a study on the management of training in basic operating rooms using new evaluation criteria [2]. However, due to the diverse types, shapes, and sizes of equipment in the training room, traditional detection and identification management systems are difficult to meet practical needs, Sturt et al. conducted a study on effective review of managers of practical training rooms using a supervisory framework [3]. Therefore, a device detection management system for IoT information training rooms on the ground of an improved YOLOV algorithm has been proposed in the study. The YOLOV algorithm is an extensively utilized algorithm in the object detection (OD) and recognition. It transforms the OD and recognition problem into a regression problem and directly forecasts the category and position of the target through a neural network. Majeed et al. conducted an in-depth study on Facial Recognition and Attendance system for monitoring system in practical training room through YOLOv5 model [4]. However, the YOLO algorithm suffers from inaccurate positioning and missed detections in some complex scenarios, thus requiring improvement Hasanvand et al. explored vehicle recognition technology using specific image processing techniques [5]. Meanwhile and other scholars conducted an optimization study on the process of detecting small targets by target detector using improved YOLOv4 network [6]. The study first uses the YOLOV algorithm to detect equipment in the IoT information training room, and then improves the YOLOV algorithm using clustering methods to enhance its detection accuracy and robustness. The IoT information training room equipment management system (TREMS) not only accurately monitors and identifies the status of the training room equipment, but also manages the reasonable utilization of equipment. This can enhance the overall effectiveness of the management system. The research aims to construct a device detection management system model that can provide effective technical support for device management in IoT training rooms. Meanwhile, it also provides new research ideas for OD and classification in other similar scenarios.

In summary, Section I and Section II of the study analyzes the training room equipment management now while summarizing the research of YOLOV algorithm in equipment detection and identification; Section III firstly improves the YOLOV algorithm by using the method of clustering, and constructs the equipment management system system model of the IoT informatized training room on the basis of the improved algorithm; the third part is to verify the performance of constructing the equipment management system model of the IoT informatized It is to verify the performance of constructing the model of equipment management system system of IOT informationization training room, and the verification of the performance is carried out with simulation experiments and practical applications; Section IV is to analyze and summarize the obtained experimental results, and to get the advantages and shortcomings of the model constructed by the research. Finally Section VI concluded the paper.

II. Related Works

The management system of training room equipment is one of the key factors in maintaining the stable and reliable development of IoT information technology training rooms. It can enhance the effective management ability of equipment in the training room. But currently, the management system of the training room still has problems such as low efficiency and longtime consumption in equipment identification. To promote the scientific development of IoT information technology training rooms, many experts and scholars have conducted in-depth research on the detection and recognition of equipment in the training rooms. To improve the detection performance of training models on device images, scholars such as Obaid I proposed a device detection and recognition method on the ground of Tiny YoloV3. This method can detect and recognize devices on the ground of the performance and execution time of the training model. The outcomes showcased that the recognition probability of large objects increased from 75% to 90%, and the detection and recognition of small objects increased by 20% [7]. Zhao J et al. proposed a data adaptive amplitude method on the ground of spatial and channel attention to enhance the utilization of priority devices in two-level neural networks. This study utilizes feature approximation to generate adaptive amplitudes and minimizes the difference between real values and 1-bit convolutions. The results showed that a 64.0% efficiency was achieved on the Pascal VOC dataset, with storage and computation savings of 18.62 times and 15.77 times, respectively. On ImageNet, storage space savings of 11.04 times and 10.80 times were achieved compared to fully accurate counterparts [8]. Chinta R et al. proposed a visual framework to improve the performance of object recognition technology. This framework can utilize novel and fast algorithms to construct frameworks for objects, and then perform deep recognition on these frameworks. The outcomes showcased that the proposed framework can be executed on a humanoid robot and also extends its self-sufficiency in learning and communicating with humans [9]. Jiaxu L and other scholars proposed a bidirectional feature fusion method for enhancing the detection performance of small targets. This method can improve the performance of small OD and recognition from different aspects such as feature fusion, context learning, and attention mechanism. The results indicate that research on feature fusion, context utilization, and attention mechanisms is of great value in improving small OD in complex scenes. The detection accuracy of small target objects was enhanced by 10.3% [10].

F Li et al. proposed a deep convolutional recognition algorithm for small targets on the ground of an improved YOLOv4 network for addressing the issue of inaccurate detection of small targets in mainstream OD. This study requires obtaining more target feature information and introducing spatial pyramid pools with different pool kernel sizes. The outcomes showcased that compared to the original YOLOv4, the improved network has increased the average detection speed and accuracy by about 30% and 7%, respectively [11]. Scholars such as S Lu proposed a real-time video OD algorithm on the ground of YOLO network to apply deep learning technology to OD and recognition. This study eliminates the influence of image background through image preprocessing, and then trains a fast YOLO model for OD for getting target information. The results indicate that the YOLO network has been improved by replacing the original convolution operation with a small one, reducing the quantity of parameters and greatly shortening the time for OD [12]. Wang K proposed a high-precision remote sensing detection method on the ground of the advanced YOLOv4 framework for enhancing the detection performance of large-scale targets. A clustering algorithm that combines object scale knowledge is studied for generating a prior anchor box with high matching degree. The feature extension module is designed for expanding the receptive domain of the backbone network and getting essential contextual information. The results indicate that the feature extension module is designed for extending the receptive domain of the backbone network and getting essential contextual information [13]. To improve the detection performance of small objects and objects with varying scales, Y Ma et al. introduced a densely connected feature pyramid strategy and constructed a scale aware attention module. The study utilizes dense network blocks and median frequency balancing mechanism to process data, and then utilizes OD algorithms for detection. The results showed that AP increased by 6.22% and 5.09%, respectively. AP is 1.82% higher than YOLOv4 [14].

In summary, the design and research of the IoT TREMS model on the ground of the improved YOLOV4 algorithm is of great significance. It uses clustering algorithm to improve YOLOV4 algorithm, analyzes the detection and recognition of equipment in the training room, and obtains the specific situation of the equipment, providing more effective information for the equipment management system. The research aims to provide effective technical support for device detection and classification in IoT training rooms.

III. Design of IoT TREMS on the Ground of Improved YOLOV4 Algorithm

The design of an IoT TREMS on the ground of the improved YOLOV4 algorithm is a comprehensive solution that combines deep learning, IoT technology, and information management technology. Its main goal is to improve the detection and recognition accuracy and efficiency of IoT training room equipment by improving the YOLOV4 algorithm, thereby providing reliable support for the management system.

A. *Research on IoT Training Room Equipment Detection and Recognition on the Ground of YOLOV4 Algorithm*

In the equipment management system of the IoT training room, equipment detection and identification are important links. In the process of device detection, the collected video and image information, as well as their clarity and resolution, will affect the judgment of device detection and recognition results. Therefore, it is necessary to increase the accuracy of data collection for IoT training room equipment. The YOLOv4 algorithm is a deep learning based image recognition technology mainly used for OD. It can recognize targets in the images of IoT training room equipment and detect whether the equipment in the training room is working properly or missing, Lou completed a study on the counting of non-contact surveillance area based on YOLOv4-tiny algorithm [15]. By detecting and identifying the equipment in the IoT training room, it is possible for ensuring the safe operation of the equipment and prevent it from being left vacant or damaged or stolen. Dewi et al. conducted an in-depth analytical study on the performance of video vehicle recognition using Yolo V4 algorithm [16]. Through research on the detection and recognition of IoT training room equipment, it has been found that if intelligent detection of equipment is carried out using images, it is necessary to collect, analyze, and calculate the detected dataset and images. To better collect equipment related data, a YOLOv4 algorithm was used to construct an IoT training room equipment detection and recognition model. The network structure diagram of YOLOv4 is showcased in Fig. 1.

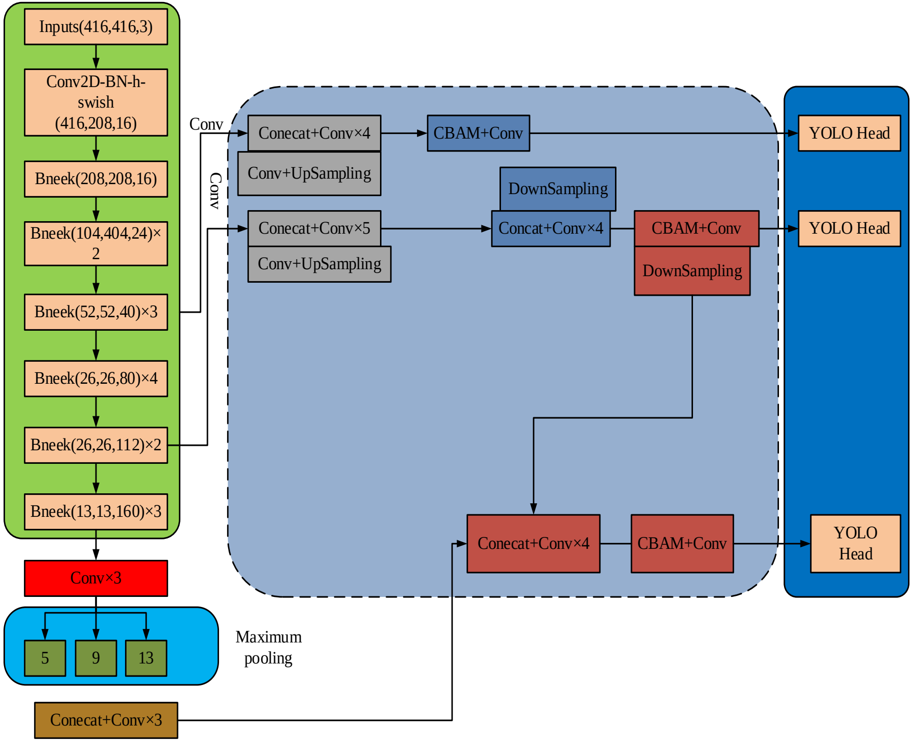


Fig. 1. Network structure diagram of YOLOv4.

When using the YOLOv4 algorithm for OD, for ensuring the accuracy of the data, it is necessary to pay attention to the convergence speed. The convergence speed refers to the speed at which a model gradually approaches the optimal solution during the training process. This speed is affected by the loss function. To improve convergence speed, research needs to consider the boundary values and confidence coefficients of the data. The boundary value of data refers to the minimum and maximum size of the target object in the dataset, which can help the model learn the size range of the target object. The confidence coefficient is used to measure the model's level of confidence in each target object. By setting reasonable boundary values and confidence coefficients, the convergence speed of the model can be accelerated, thereby improving the accuracy of the data. When traditional algorithms perform regression on bounding boxes, the coordinates of the center point and the width and height data are used as independent variables for calculation, Li and other scholars combined YOLOv4 with attention mechanism for the study of traffic sign detection in clothing context [17]. To reduce this part of the error, the study abandoned the least squares method and used the Jaccard index to solve the variable relationship between the parameters and the center coordinate. And on the ground of the problems with the Jaccard index, corresponding optimizations were made to the target detection loss function, the distance loss function between the predicted box and the true box in the target detection model, the target detection loss function, and the confidence loss function. The Jaccard index can be expressed using Formula (1).

$$L_{Jaccard} = 1 - Jaccard(A, B) \qquad (1)$$

In Formula (1), A, B respectively represent the difference in IOU in the predicted box and the true box. The improved OD loss function incorporates a penalty term, which can prevent gradient problems during data detection and can be represented by Formula (2).

$$L_{GIOU} = 1 - IOU + \frac{\left|C - B \cap B^{gt}\right|}{|C|} \qquad (2)$$

In Formula (2), B represents the true box value. C is the minimum bounding box generated by the intersection of A, B. B^{gt} represents the center point of the true box value. Due to the insufficient calculation of area in the process of OD loss function, it is necessary to use the loss function of the distance in the predicted box and the actual box in the OD model for representing the relationship in the predicted value and the actual value. This can also increase the convergence process of the loss function. Formula (3) can be used to represent the loss function of the distance in the predicted box and the true box in the OD model.

$$L_{DIOU} = 1 - IOU + \frac{\rho^2(b, b^{gt})}{c^2} \tag{3}$$

In Formula (3), c represents the diagonal length that covers the minimum range in the true value and the predicted value. ρ is a constant. b^{gt} represents the coordinates of the center point. The improvement of the target detection loss function mainly involves optimizing the overlap area, spacing at the center position, and the ratio of length and width in the coverage area. It can be represented by Formula (4).

$$\begin{cases} LCIOU = 1 - IOU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \\ \alpha = \frac{v}{(1 - IOU) + v} \\ v = \frac{4}{\pi}(\arctan\frac{\omega^{gt}}{h^{gt}} - \arctan\frac{\omega}{h})^2 \end{cases} \tag{4}$$

In Formula (4), ω^{gt} serves as the width of the true value. h^{gt} serves as the height of the true value. b^{gt} serves as the coordinates of the center point. ω represents the width of the predicted value. α represents the trade-off parameter. v represents the consistency between the candidate value and the aspect ratio of the target object. ρ is a constant, representing the Euclidean distance. The confidence loss function can be calculated using Formula (5).

$$\begin{cases} L_{cla}(O, C) = -\sum_{i\in Pos}\sum_{i\in cla}(O_{ij}\ln(\hat{C}_{ij}) + (1 - O_{ij})\ln(1 - \hat{C}_{ij})) \\ \hat{C}_{ij} = Sigmoid(C_{ij}) \end{cases} \tag{5}$$

In Formula (5), O_{ij} represents a constant, with a value of 1 or 0. $\hat{C}_{ij}$ represents the probability that the predicted value i contains the j target. The entire process of detecting equipment in the YOLOv4 IoT training room mainly consists of three parts: creating a dataset, training the dataset, inputting it into the model to calculate the confidence of the results. The entire process is shown in Fig. 2.

B. *Construction of Equipment Management System Model on the Ground of Improved YOLOV4 Algorithm*

Through the study of YOLOv4 algorithm in device detection and recognition, it was found that the backbone network CSPDarknet in YOLOv4 has greatly improved in performance. However, it is still a heavyweight network that cannot meet the requirements of low consumption and high efficiency in the detection and recognition process. Zhang utilized YOLOv4 for the recognition study of the posture of welding studs [18]. Although YOLOv4 has significant advantages in the model of device detection and recognition in IoT training rooms, there is still a problem of excessive training parameters in the actual operation process, Liu and other scholars utilized YOLOv5 algorithm for fast detection study of infrared device images [19]. To solve this problem, the K-means clustering algorithm was applied to the prior boxes of the YOLOv4 algorithm dataset to cluster the data. K-means clustering can first select the center point of the initial cluster in the prior box, and then perform clustering. Meanwhile, due to the uneven scale distribution in the detection image, K-means clustering can forcibly cluster objects of similar sizes, thereby improving the accuracy of detection. The perspective scale for identifying cameras in the IoT training room equipment detection management system is fixed. This study utilizes K-means clustering to cluster different specific sizes, but it still needs to meet the requirements of sample clustering. The requirements for clustering can be expressed using Formula (6).

$$D \sim u(0, r) \tag{6}$$

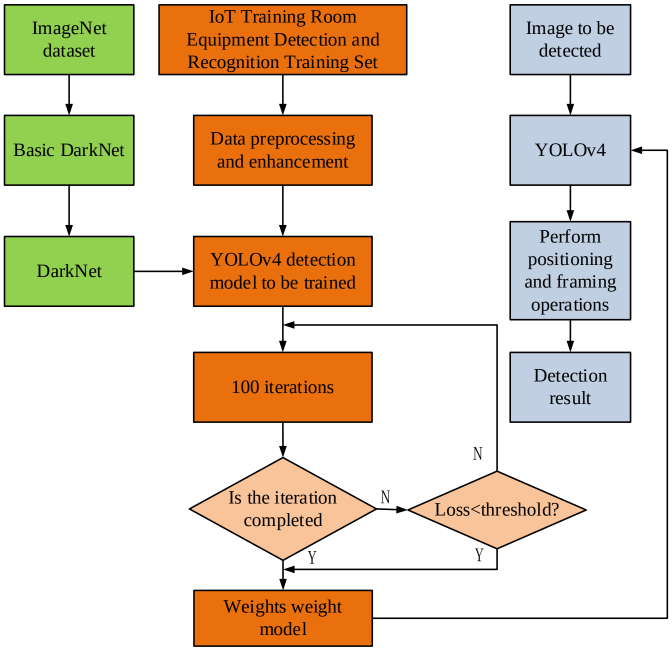

ImageNet dataset
IoT Training Room Equipment Detection and Recognition Training Set
Image to be detected
Basic DarkNet
Data preprocessing and enhancement
YOLOv4
DarkNet
YOLOv4 detection model to be trained
Perform positioning and framing operations
100 iterations
Detection result
N
Is the iteration completed
N
Loss<threshold?
Y
Y
Weights weight model

Fig. 2. Detection flowchart on the ground of YOLOv4 algorithm.

In Formula (6), $D = (d_1, d_2, \cdots, d_n)$ represents the prior box. r represents the image resolution of the clustering input. $u(0, r)$ represents the size range of the recognition device. There are a total of three groups and nine prior boxes in YOLOv4 used in the study. These three sets of prior boxes can detect and recognize devices of different sizes, including large, medium, and small, as set. To avoid the phenomenon of undetectable size, the study only selected one detection head, which means that all devices are placed on a certain layer for detection, to avoid undetectable situations. Meanwhile, to prevent situations where the device volume is too small and cannot be detected, the study added IK-means on the basis of K-means clustering. This enables clustering of all nodes in the network and sets two thresholds, Sun et al. utilized YOLO algorithm for effective detection of targets at multiple scales to improve the accuracy of different picking devices [20]. This allows for scale division of devices of different sizes. Through the detection of three sets of prior boxes, a total of nine prior boxes were obtained. Two threshold values were set to annotate the size of the object boxes, and rectangular annotation boxes were defined. The size of this annotation box is defined using the length of the diagonal, and the specific definition formula can be represented by Formula (7).

$$Diag(j)=\sqrt{(a_j^w)^2+(a_j^h)^2} \tag{7}$$

In Formula (7), $(a_j^w)^2+(a_j^h)^2$ represents a rectangular annotation box. $j=1,2,\cdots,m,$. m represents the total amount of all annotation boxes. $Diag(j)$ represents the diagonal length corresponding to the annotation box. w represents width. h represents height. After obtaining the length of the diagonal, clustering algorithms can be used to cluster the diagonal and obtain different detection box cluster centers. After calculating the cluster center, it can be utilized for determining the threshold that needs to be set for the research. The calculation of threshold can be represented by Formula (8).

$$\begin{cases} Th_1=(C_1+C_2)/2 \\ Th_2=(C_2+C_3)/2 \end{cases} \tag{8}$$

In Formula (8), $C=(C_1,C_2,C_3)$ represents the cluster center. Th_1 and Th_2 represent threshold 1 and threshold 2. The flowchart of using K-means combined with IK-means clustering is shown in Fig. 3.

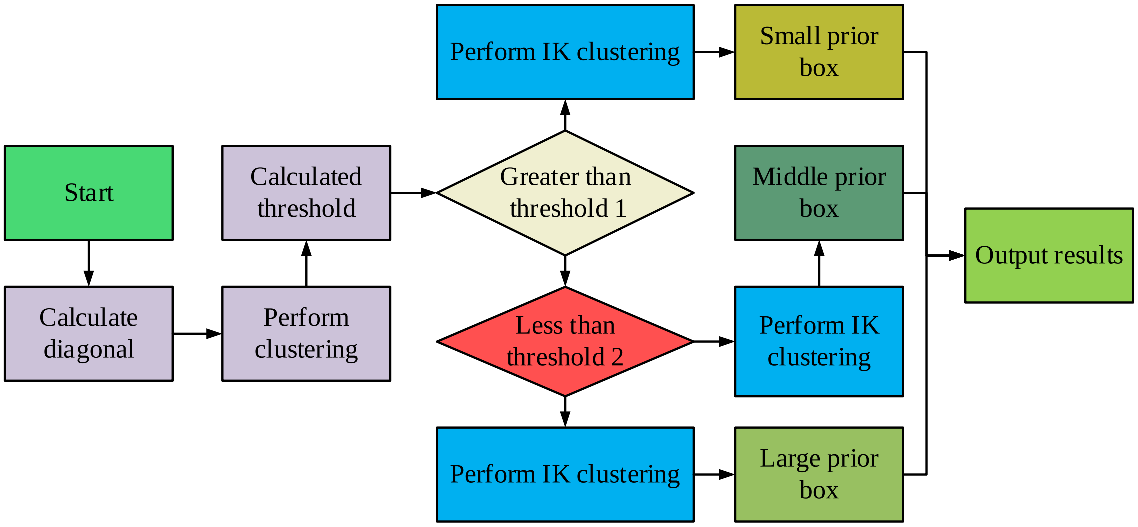


Fig. 3. Flowchart of K-means combined with IK-means clustering.

To further ensure the high detection accuracy of the model, attention modules were introduced into the backbone network of the model. The addition of attention modules could enhance the learning efficiency and detection and recognition accuracy of the model for data information. Meanwhile, to reduce the impact of dimensionality reduction on the attention module channels, the study eliminated the dimensionality reduction effect by performing lightweight operations on the attention module. The attention module at this point can be represented by Formula (9).

$$W(k)=\begin{bmatrix} w^{1,1} & \cdots & w^{1,k} & 0 & \cdots & 0 \\ 0 & w^{2,2} & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & w^{C,C-k+1} & \cdots & 0 & w^{c,c} \end{bmatrix} \tag{9}$$

In Formula (9), k serves as the size of the convolution kernel in the module. C represents the number of channels for inputting feature maps in the module. At this point, the shared weight values of all channels can be represented by Formula (10).

$$w_i=\sigma(\sum_{j=1}^{k} w_i^j y_i^j),y_i^j\in\Omega_i^k \tag{10}$$

In Formula (10), σ represents the activation function. y_i represents weight. Ω_i^k represents the k domain channels in the y_i weight. The schematic diagram of the attention module structure is showcased in Fig. 4.

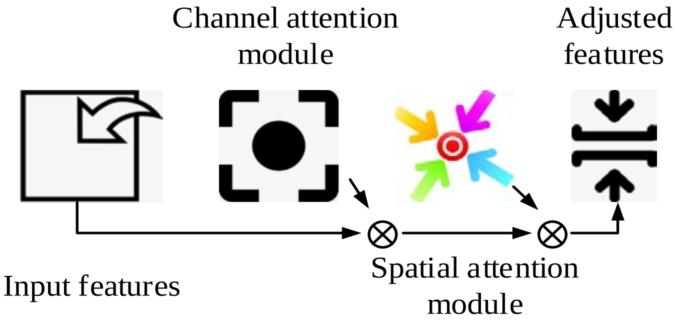


Fig. 4. Schematic diagram of the structure of the attention module.

In summary, the IoT information training room equipment detection on the ground of the improved YOLOV4 algorithm first improved the prior boxes using K-means clustering, then added attention modules to the backbone network and removed the SPP structure in the YOLOV4 network. The flowchart of the device detection and recognition system in the improved YOLOV4 algorithm device management system is shown in Fig. 5.

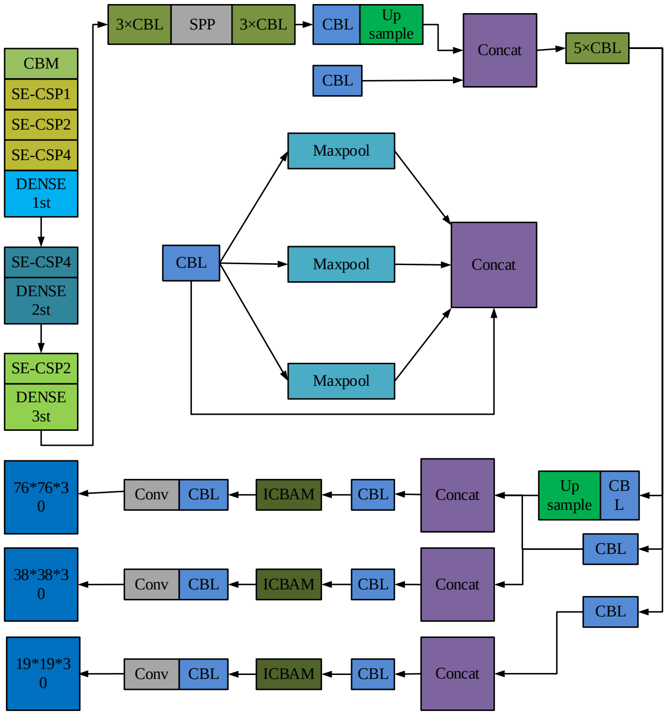


Fig. 5. Flowchart of equipment detection and identification system in equipment management system with improved YOLOV4 algorithm.

On the ground of the analysis in Fig. 5, after the model training is completed, it is necessary to use mAP in the target domain as an evaluation indicator. mAP can be represented by Formula (11).

$$mAP = \frac{1}{N}\sum_{i=0}^{N-1} AP_i \tag{11}$$

In Formula (11), N represents the category of the detected target, with a value of 3. AP_i represents the AP value corresponding to the three types of detection targets.

IV. Performance Analysis of Equipment Management System Model on the Ground of Improved YOLOV4 Algorithm

To verify the performance of the IoT information training room equipment detection management system model on the ground of the improved YOLOV4 algorithm, this study compared the YOLOV4 algorithm and Single Shot Multibox Detector (SSD) with the improved YOLOV4 algorithm as comparative methods. This is to verify the performance of the IoT information TREMS on the ground of the improved YOLOV4 algorithm in equipment detection and recognition.

A. *Performance Analysis of Equipment Inspection Management System Model*

To verify the performance of the equipment management system model in the IoT information training room in equipment detection and recognition, the performance of the model was analyzed. It takes the loss value during the training process of the system model as one of the indicators to judge the performance of the model. The comparison results of function loss values for three methods in device detection and recognition are shown in Fig. 6.

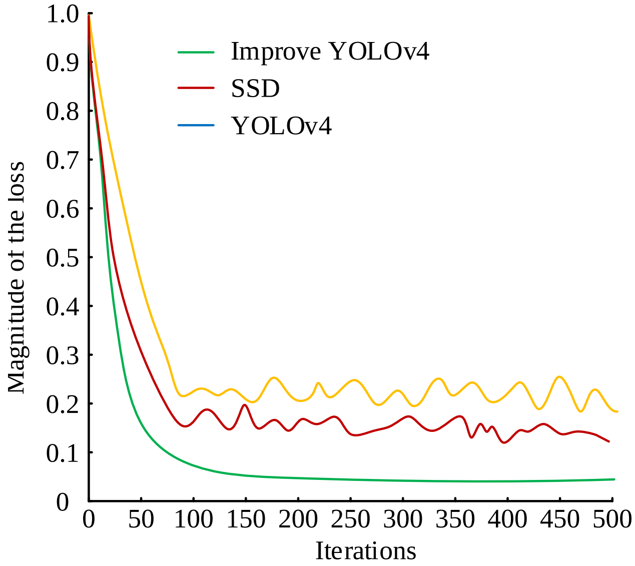
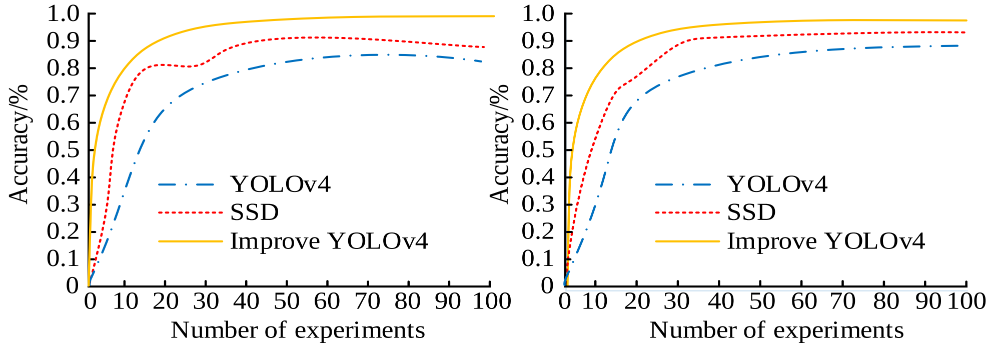


Fig. 6. Comparison results of function loss values among three methods for device detection and recognition.

Fig. 6 showcases that the loss value of improved YOLOv4 tends to stabilize after 146 iterations, with a loss value of 0.16. The loss value of SSD slows down after 98 iterations, but does not tend to stabilize. Instead, it remains fluctuating, with a loss value of 0.25. The loss value of YOLOv4 slows down after 95 iterations, but does not tend to stabilize, with a loss value of 0.31. This indicates that the smaller the difference between the predicted and actual values in the processing of device data, the more accurate the predicted results of the device management system model constructed in the study. To verify the performance of the model in device image detection and recognition, the accuracy and recall of recognition were studied as validation indicators. The comparison results of recognition accuracy and recall of the three methods are showcased in Fig. 7.

Fig. 7(a) shows that there is a certain difference in the accuracy of device recognition among the three methods. The improved YOLOv4 has a device recognition accuracy of 95.71%, SSD has a device recognition accuracy of 88.64%, and YOLOv4 has a device recognition accuracy of 81.52%. Fig. 7(b) shows that among the three methods, the improved YOLOv4 has the highest recall rate for device recognition data, which is 92.83%. The recall rate of SSD is 88.31%, and the recall rate of YOLOv4 is 82.9%. This indicates that the improved YOLOv4 system model constructed in the study has stronger robustness in data detection. To verify the recognition performance of the system model on devices, the study used device recognition false alarm rate and mAP as indicators. The comparison results of the false alarm rate and mAP for device recognition using three methods are shown in Fig. 8.

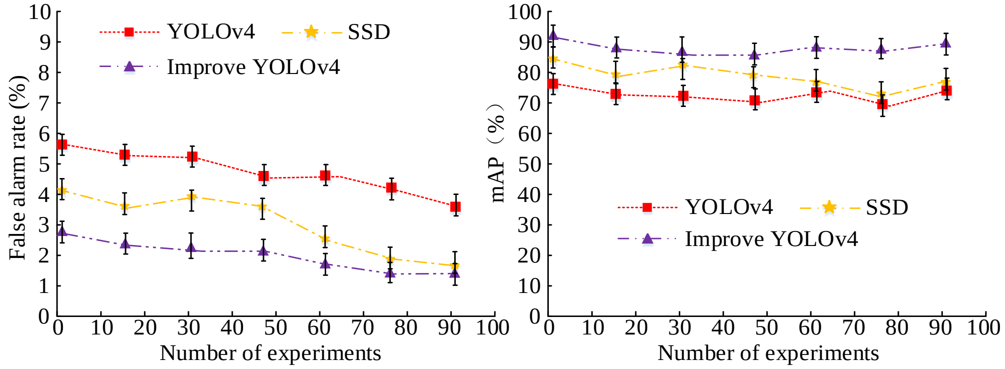
Fig. 8(a) shows that during the equipment detection and recognition process in the IoT information training room, the improved YOLOv4 has a false alarm rate of 2.15%. The device detection and recognition false alarm rate of SSD is 3.95%, and the device detection and recognition false alarm rate of YOLOv4 is 5.26%. Fig. 8(b) shows that the improved device detection and recognition mAP for YOLOv4, SSD, and YOLOv4 are 91.66%, 82.39%, and 78.24%, respectively. This indicates that the system model constructed in the study can significantly reduce errors in equipment detection and recognition processes, and improve detection performance. To further validate the system model, the quantity of floating-point operations per second and the number of frames transmitted per second of the image were used as indicators for performance validation. As shown in Fig. 9, the comparison results of three methods on the quantity of operations and the quantity of transmitted frames are presented.



(a) Accuracy of different methods

(b) Recall rates for different methods

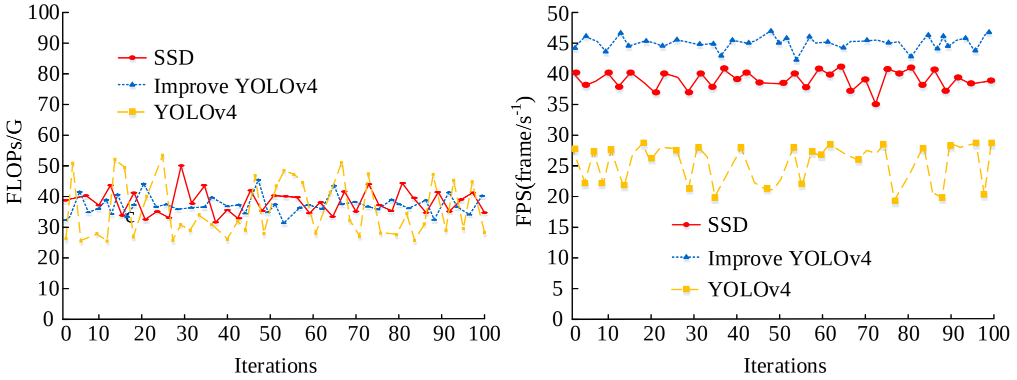
Fig. 7. Comparison results of recognition accuracy and recall of three methods.



(a) Device recognition false alarm rate using different methods

(b) Comparison results of mAP using different methods

Fig. 8. Comparison of false alarm rates and mAP results of three methods for device recognition.



(a) Comparison results of floating-point operations for device detection and recognition using different methods

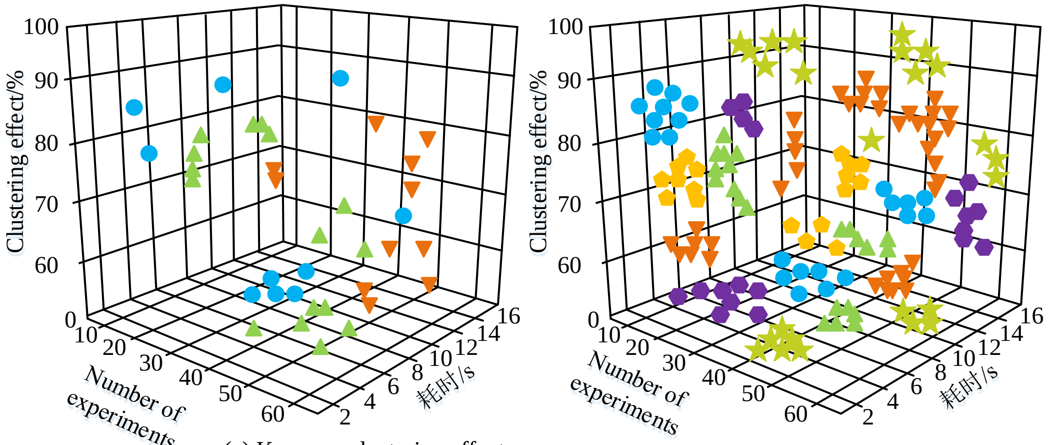
(b) Comparison results of transmission frame rates for device detection and recognition using different methods

Fig. 9. Comparison results of three methods on the number of operations and transmission frame rate.

Fig. 9(a) shows that there is a certain difference in the number of floating-point operations per second among the three methods when detecting devices in the IoT information training room. The budget for improving YOLOv4, SSD, and YOLOv4 is 42.36, 36.25, and 31.83, respectively. Fig. 9(b) shows that the transmission frame rate plays a crucial role in image monitoring and recognition. The improved YOLOv4 has a detection and recognition transmission frame rate of 43.59 for device images, while SSD and YOLOv4 have a detection and recognition transmission frame rate of 38.17 and 24.93 for device images, respectively. This indicates that the management system model has better performance and stronger adaptability in the recognition process of device images.

B. *Application Performance Analysis of Equipment Inspection Management System Model*

To verify the application performance of the IoT information technology TREMS in equipment detection, a study was conducted to compare the clustering results of equipment detection and recognition data, and the clustering effect was used as the validation indicator. The comparison results of K-means and system model clustering performance are shown in Fig. 10.



(a) K-means clustering effect

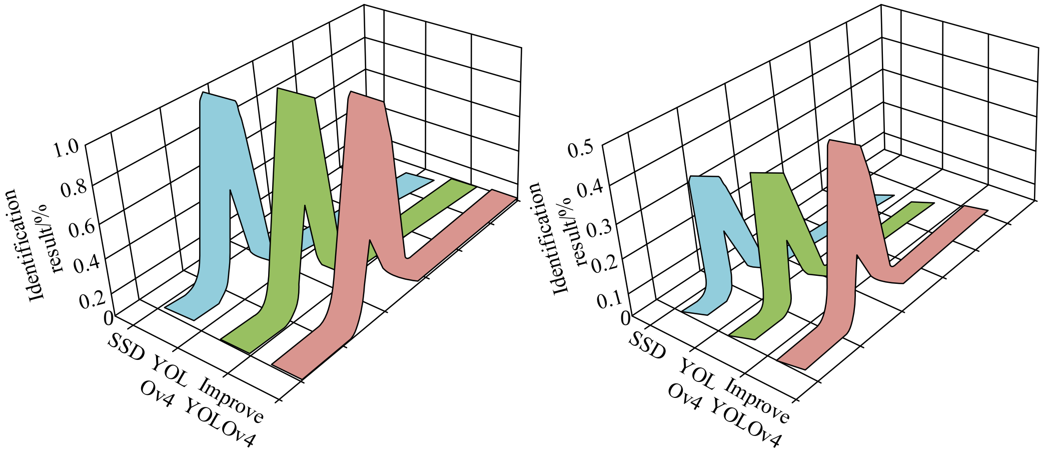
(b) Detection and recognition system model clustering effect

Fig. 10. Comparison of clustering performance between K-means method and system model.

Fig. 10(a) shows that in the K-means clustering results, a total of three types of device information were found, taking a total of 12.8 seconds. Through analysis, it was found that the clustering method did not have a good overall recognition effect on the equipment in the IoT information training room. Fig. 10(b) shows that during the detection and recognition process of IoT information training room equipment in the system model, a total of 6 types of equipment were identified, which is much higher than the clustering results of K-means. Simultaneously detecting and recognizing takes 9.5 seconds. This indicates that the IoT information training room equipment detection management system constructed through research has a better effect on data clustering and can improve the performance of equipment detection and recognition. To further validate the performance of the system model, environmental conditions were studied as validation indicators. The device detection and recognition performance of the system model was validated in bright and dim environments, as showcased in Fig. 11, which showcases the detection and recognition outcomes of three methods in two different environments.

Fig. 11(a) shows that in a brightly lit environment, all three methods have good performance in detecting and recognizing devices. The improved YOLOv4 achieved a recognition result of 97.05%, SSD achieved a recognition result of 92.46%, while YOLOv4 achieved a relatively poor recognition result of 87.69%. Fig. 11(b) shows that in a dim environment, the detection and recognition outcomes of the three methods on the device are significantly affected. The recognition results of improved YOLOv4, SSD, and YOLOv4 were 46.95%, 38.31%, and 31.28%, respectively. Through comparison, it was found that the detection capability of the equipment management system model has significant advantages compared to the comparative methods. For further verifying the application performance of the system model, the recognition scalability of the system model was analyzed. As shown in Fig. 12, three methods were applied to analyze the clustering ability in device detection and recognition. The curve in the figure represents the iterative process of clustering, the graph on the right shows the clustering model, and the orange in the figure represents the clustering center.

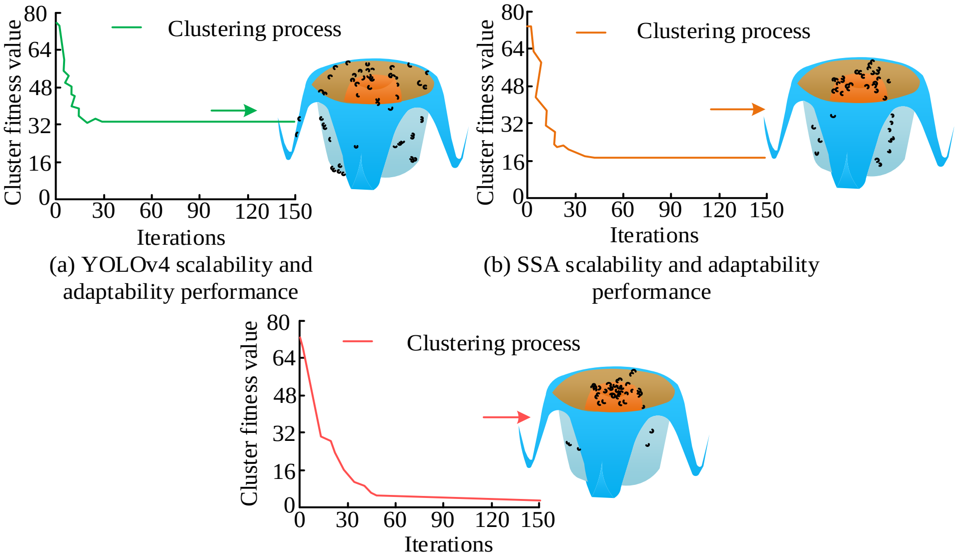
Fig. 12(a) shows that the YOLOv4 method stopped clustering analysis of the data after 31 iterations, and the entire clustering process was relatively scattered, with fewer trajectory points in the orange position. Fig. 12(b) shows that the SSD method stopped analyzing the clustering data after 52 iterations. Fig. 12(c) shows that the improved YOLOv4 method stopped analyzing clustering data at 49 iterations, but it had the most trajectories in the orange region, with only four trajectories outside the orange region. This indicates that the improved YOLOv4 method has a more stable applicability performance in clustering data.



(a) The detection and recognition results of three methods in bright environments

(b) The detection and recognition results of three methods in dim environments

Fig. 11. Three methods for detecting and identifying equipment in two different environments.



(a) YOLOv4 scalability and adaptability performance

(b) SSA scalability and adaptability performance

(c) Improving YOLOv4 scalability and adaptability performance

Fig. 12. Application analysis of three methods for clustering ability in equipment detection and recognition.

V. Discussion

In the research on the management system of the IoT information technology training room based on the improved YOLOV4 detection and recognition algorithm, there may be challenges such as difficulties in data collection, algorithm optimization, hardware and equipment limitations, data security and privacy issues, and difficulties in verifying practical application scenarios. These challenges may affect the progress of the research and the accuracy of the results, which requires researchers to continuously improve and optimize the research methodology to ensure that the final research results can be effectively applied and verified. Through related research, it is found that the potential future directions of research mainly include algorithm optimization, multi-target detection, behavior recognition, multi-sensor fusion, scenario-oriented optimization, system integration and deployment, and privacy protection and data security. These directions will help to further enhance the intelligence level of the management system of the IoT informatized training room and improve the management efficiency and security.

VI. Conclusion

To enhance the management ability of the IoT information training room management system, a study was conducted on the equipment management system of the training room. It proposed a system model for equipment detection and management in IoT information training rooms on the ground of an improved YOLOV4 algorithm. The results showed that the system model identified a total of six types of devices in the detection and recognition process of IoT information training room equipment, with a detection and recognition time of 9.5 seconds. In bright environments, the improved YOLOv4 achieved a recognition result of 97.05%, while in dim environments, the improved YOLOv4 achieved recognition results of 46.95%, and its adaptability was significantly better than the comparison method. This indicates that the system has high accuracy and robustness in device detection and recognition, and can meet the needs of users for device management. Meanwhile, the system can perform real-time detection and identification of equipment in the training room, thereby improving the ability of equipment management and effective utilization. However, there are still certain shortcomings in the research, and there is still room for optimization of equipment detection and recognition algorithms in the IoT information training room. By optimizing the algorithm, the performance of detection and recognition could be further enhanced, providing more data support for training room managers.

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Diagnosing Autism Spectrum Disorder in Pediatric Patients via Gait Analysis using ANN and SVM with Electromyography Signals

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***Abstract*—Autism Spectrum Disorder (ASD) is a permanent neurological maturation condition that impacts communication, social interaction, and behavior. It is also associated with atypical walking patterns. This study aims to create an automated classification model to distinguish ASD children during walking based on the muscles Electromyography (EMG) signals. The study involved 35 children diagnosed with ASD and an equal number of typically developing (TD) children, all aged between 6 and 13 years. The Trigno Wireless EMG System was used to collect EMG signals from specific muscles in the lower limb (Biceps Femoris - BF, Rectus Femoris - RF, Tibialis Anterior - TA, Gastrocnemius - GAS) and the arm (Biceps Brachii - BB, Triceps Brachii - TB) on the left side. To identify the most significant features influencing walking in ASD children, a statistical analysis using the Mann-Whitney Test was conducted. The dataset contained 42 features derived from the analysis of six muscles across seven distinct walking phases throughout a single gait cycle. Following this, the Mann-Whitney Test was utilized for feature selection, uncovering five significantly distinctive features within the EMG signals between children with ASD and those who were typically developing. The most notable EMG features were subsequently employed in constructing classification models, namely an Artificial Neural Network (ANN) and a Support Vector Machine (SVM), aimed at distinguishing between children with ASD and those who were typically developing. The results indicated that the SVM classifier outperformed the ANN classifier, achieving an accuracy rate of 75%. This discovery shows potential for employing EMG signal analysis and classification model algorithms in diagnosing autism, thereby advancing precision health.**

Keywords—Autism Spectrum Disorder; Electromyography signals; Artificial Neural Network; Support Vector Machine; precision health

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a lifelong neurodevelopmental condition distinguished by speech impairments, atypical behaviors, and difficulties in social communication. Certain children diagnosed with ASD may display motor-related challenges concerning gross motor skills, encompassing issues with motor coordination, muscle tone, arm movement, postural stability and gait. These motor difficulties are linked to the intricate interplay between the neurotransmitter system and specific brain structures, which influence both basic motor skills and sensory-motor performance [1]. Typically, children with ASD display distinct gait patterns, often characterized by clumsiness [2], subtlety, and a wide base [3-4]. In some cases, children with ASD may exhibit toe-walking tendencies, which are more closely associated with motor behavior than language development. Therefore, early detection of ASD can rely on motor indicators [5-6]. Children with ASD may experience motor delays in gross and fine motor skills, affecting their locomotion [2, 7].

Electromyography (EMG) is an experimental methodology employed in the development, recording, and analysis of myoelectric signals. Its application, particularly in the biomedical field, has grown significantly. EMG-based models have provided accurate results in adjusting musculoskeletal geometry, such as muscle-tendon lengths, velocities, and arm moments for individuals with high-functioning hemiparesis during walking [8]. EMG signal analysis can also measure variations in EMG waveforms during different walking conditions, contributing to human-machine interactions and the adaptability of locomotion activities [9]. Research indicates a notable decrease in the activity of hip adductors and hamstring muscles during walking among individuals with wider pelvises [10].

Gait, the method by which walking occurs, can undergo clinical assessment through various means, such as laboratory tests like surface EMG, force plates, and kinematic assessments. The central nervous system plays a pivotal role in transmitting commands that activate the muscular system, ultimately facilitating movement. Measuring muscular activity through non-invasive EMG is a suitable method for characterizing motor activity [11]. The application of EMG in the rehabilitation of central neurological disorders, including autism and cerebral palsy, has demonstrated successful outcomes [12-13].

The perceptron-based technique employs algorithms rooted in the perceptron concept, encompassing single-layered perceptrons, multi-layered perceptrons, and Radial Basis Function (RBF) networks [14]. Between these, Artificial Neural Networks (ANN), a subtype of multi-layered perceptrons, has gained prominence in the analysis of EMG signals in various applications related to human gait, including classification [15, 16], prediction of gait angles [17, 18], and

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muscle activation [15, 19]. ANN algorithms have been developed to bridge the gap between kinematic movement planning and human muscle activation for normal locomotion. These algorithms adjust parameters such as stance width, stride length, cadence and foot clearance [20]. Wang [15] developed an ANN-based model to address the challenge of accurate muscle activation prediction, showing a strong relationship between EMG signals and joint moments [15]. ANN has been widely used for gait pattern classification [17, 21-22]. Jung [22], for example, applied neural networks to classify gait phases for controlling exoskeleton robots, demonstrating superior performance compared to traditional gait classification methods using foot sensors. ANN has also proven effective in distinguishing between healthy individuals and those with pathological gait, as it can identify relevant parameters specific to classification tasks [17]. Thus, ANN is a valuable tool for gait classification.

The Support Vector Machine (SVM) is a widely employed machine learning technique utilized for data analysis, classification and pattern recognition. SVM algorithms have been applied in numerous studies involving EMG signal analysis [23-26]. SVM has shown potential as a classifier for developing fully automatic EMG signal analysis systems for clinical use. It has successfully identified neuromuscular diseases with a classification accuracy of 100% by combining multi-class SVM algorithms with autoregressive (AR) features [24]. SVM algorithms have also excelled in distinguishing various human activities based on EMG signal data. An SVM classifier utilizing AR-based features attained a recognition rate more than 90% for activities like standing still, walking, running and jumping, and surpassing the performance of conventional SVM classifiers [26]. EMG signals have even been used for hand gesture recognition, with bend resistive sensors and SVM classifiers achieving a classification accuracy of 93.33%, making it suitable for communication by soldiers [27].

Notably, there has been limited attention given to the automated classification of ASD children based on EMG signals. Therefore, this study aims to differentiate between ASD and typically developing (TD) children using EMG signal analysis during walking. The lower limb and arm muscles examined in this study include Biceps Femoris (BF), Rectus Femoris (RF), Tibialis Anterior (TA), Gastrocnemius (GAS), Biceps Brachii (BB), and Triceps Brachii (TB). At the conclusion of this study, two classification models, namely ANN and SVM, were trained to distinguish EMG signals between children with ASD and typically developing children. The research seeks to assist medical practitioners in diagnosing ASD in children based on EMG signals from lower limb and arm muscles during walking, as there is currently no definitive medical test for ASD diagnosis [19].

II. Methodology

This section provides an in-depth explanation of the proposed classification system illustrated in Fig. 1. The system comprises four key stages: EMG data acquisition, pre-processing techniques, data selection and extraction methods, and the development of the classification model.

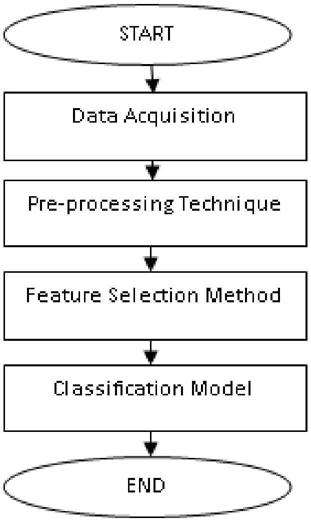

Fig. 1. Overall flowchart.

A. Data Acquisition

In this study, 35 children diagnosed with ASD and 35 typically developing children, aged between 6 and 13 years, with no history of orthopedic surgery, participated. All participants, both ASD and TD, displayed the capability to follow oral guidance given by the researcher. The ASD children were recruited from the National Autism Society of Malaysia (NASOM) center, local kindergarten and primary school in Selangor. The research procedures received ethical approval from the local ethics committee of Universiti Teknologi MARA (UiTM) in Shah Alam, Selangor, Malaysia, from May 29, 2015, to 2023 with updated database. Additionally, all participants were provided with written informed consent forms before participating.

EMG data were collected while the subjects walked naturally at a normal pace. The EMG signals were recorded using the Trigno Wireless EMG System, a product of Delsys Inc. This system is specifically designed for reliable and consistent detection of EMG signals while minimizing noise interference. Each EMG sensor in the system is equipped with a built-in triaxial accelerometer, has a communication radius of 40 meters, and features a rechargeable battery with a minimum runtime of seven hours. The system can transmit data to EMG Works Acquisition and Analysis software and supports up to 16 EMG sensors (measuring 37mm x 26mm x 15mm) and 48 accelerometer analog channels, facilitating integration with Vicon motion capture and data acquisition systems. Furthermore, the system offers full triggering capabilities, expanding the potential for integration with additional measurement technologies.

During data collection, surface electrodes were used, and their placement followed the SENIAM convention system, ensuring that the distance between electrodes did not exceed one-fourth of the muscle fiber length [28]. Specifically, 12 EMG sensors were affixed to the subjects' skin to capture EMG signals from the muscles of BF, RF, TA, GAS, BB, and TB. To secure the electrodes during the experiments, self-adhesive tapes were applied to the skin above the selected muscles, as depicted in Fig. 2.

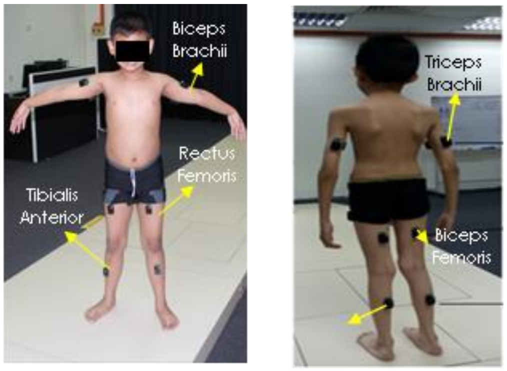

Fig. 2. Electrode placement on subject.

A securely positioned video camera was synchronized with the EMGWorks 4 Acquisition software to allow simultaneous recording of both movement and EMG data. This ensured synchronization in timing between the video camera and the software. To maintain consistency, a sample rate of 2000 Hz was chosen for recording, a rate achievable by all devices in this setup. EMG data for a single gait cycle was extracted and normalized as a percentage of the entire gait cycle duration. In this study, a gait cycle was defined as the duration between two consecutive heel strikes of the same leg. It's important to note that only EMG signals from the left lower limbs and arm muscles were considered for analysis in this study.

B. *Pre-processing Techniques*

At this stage, the raw EMG signals were normalized to a single complete gait cycle to minimize the influence of environmental noise that might have been present during data collection. Time normalization was selected as the most reliable method to enhance the quality of gait cycle analysis for EMG signal data [29]. It's important to note that each subject had varying time frames due to differences in walking speed and step length. To address this, EMG signal data for each muscle was controlled to fit within one gait cycle, ensuring consistency and obtaining standardized EMG signals for gait analysis.

In this study, a complete gait cycle was defined as the duration from the left foot's initial contact to its terminal swing. This definition was applied due to the generally insignificant differences in gait parameters between the left and right legs during normal walking [30]. The EMG signals obtained via the EMG Works Acquisition software and the duration of one gait cycle from the video camera were synchronized.

Fig. 3 and Fig. 4 illustrate the phases of the gait cycle and arm movements during normal walking, respectively. During walking, the ipsilateral arm and leg exhibit an anti-phase relationship, with the left leg in flexion and external rotation while the left arm is in internal rotation and extension. When one arm moves forward, the corresponding leg and torso move forward, and this relationship alternates between the left and right sides [31]. As walking speed increases, the contribution of active muscles to arm movements increases, while the total energy consumption decreases [31]. A previous study [32] has demonstrated that arm swinging during walking contributes to the stability of human gait.

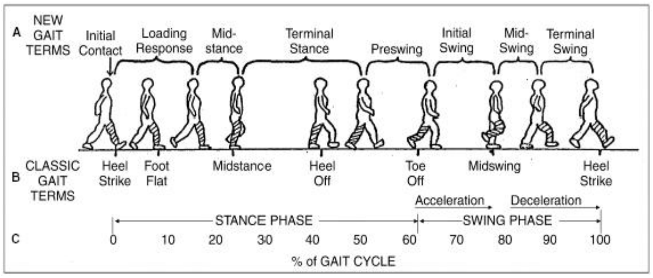

Fig. 3. Phases of one gait cycle.

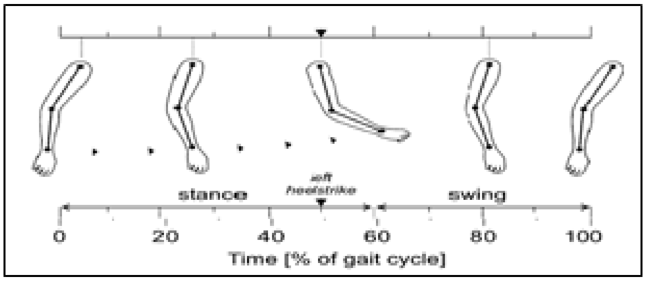

Fig. 4. Arms swing during normal walking [34].

The gait cycle normalization in this study involved two steps. The first step was time-normalizing the EMG signal data for the relevant muscles of all subjects to one gait cycle, expressed as a percentage. The time taken to complete one gait cycle in the recorded video was equated with the time frame of the acquired data. The 100% gait cycle represents the time taken for one complete gait cycle [33]. The second step involved averaging the normalized EMG signal data for the same muscle across all subjects. The normalization process for EMG signal analysis was conducted using Microsoft Excel software version 2013 (Microsoft Corp., USA). This study analyzed the tested muscles across seven gait phases: loading response (LR) spanning 0% to 10% of the gait cycle, mid-stance (MST) covering 10% to 30%, terminal stance (TST) ranging from 30% to 50%, pre-swing (PSW) encompassing 50% to 60%, initial swing (ISW) spanning 60% to 70%, mid-swing (MSW) ranging from 70% to 90%, and terminal swing (TSW) from 90% to 100% of the gait cycle.

C. *Feature Selection Method*

The feature selection process involved identifying a new set of muscles comprising the most significant features to differentiate between ASD and TD children [34], subsequently enhancing the classification performance. Initially, the normalized EMG data were subjected to an examination of normality using the Shapiro-Wilk test. This test was employed to assess whether the dataset exhibited a normal distribution or not. Given the relatively small number of subjects, the Shapiro-Wilk test is considered an appropriate method to determine the normality of the data. This test is particularly accurate and reliable in assessing the normality of scores [35]. Subsequently, non-parametric testing was applied since the data distribution in this study was found not to be normally distributed [35]. The study utilized the Mann-Whitney test with a 95% confidence interval to explore significant features within the EMG data of muscles including Biceps Brachii (BB), Rectus Femoris (RF), Gastrocnemius (GAS), Biceps Femoris (BF), Tibialis Anterior

(TA), and Triceps Brachii (TB) during walking, comparing children diagnosed with ASD and typically developing children.

D. Classification Model Development

This research presented two classification models: the Artificial Neural Network (ANN) and the Support Vector Machine (SVM); with the aim of distinguishing between ASD walking patterns and normal walking patterns. The computation of these algorithms was carried out using Matlab software version R2014a for evaluation. The input data for both classification models were derived from the significant muscle features that differed between ASD and TD children. The division of input-output data was based on the cross-validation method, where the output represented the classification group for each condition, with '0' indicating ASD and '1' indicating TD children.

One of the most commonly used techniques to assess the performance of the proposed classifier is stratified k-fold cross-validation. In this study, five-fold cross-validation was conducted. This means that the original sample was randomly divided into five equal-sized subsamples. One of these subsamples was used as the training data, while the remaining four subsamples were retained as validation data to test the model. This process was repeated five times, corresponding to the number of folds. Each observation was used for both training and validation, but only once for validation in each fold [36]. It is worth noting that the use of K-fold cross-validation is a reliable method and has the potential to provide meaningful results for estimating expected utilities [37].

For the ANN classification model, the number of hidden neurons in the hidden layer was set to achieve the best accuracy for adjusting the network weights. Scaled Conjugate Gradient (SCG) training algorithm, the optimum number of 10 neurons are found to be the optimum model accuracy. The selection of the network architecture involved testing the performance of the network by varying the number of hidden neurons from 1 to 11 in two-interval increments. The scaled conjugate gradient method was employed to train the network, which updates weight and bias values.

Regarding the SVM classification model, the input data were trained using name-value pair arguments for the kernel function. In this study, the linear kernel function, also known as the dot product, was used to obtain the best accuracy. Subsequently, each row of the sample data was classified using the information in the SVM classifier structure. The performance of both the ANN and SVM classification models was evaluated using a confusion matrix, which included measures such as accuracy, precision, sensitivity, and specificity.

III. Results and Discussion

In this segment, we will examine the acquired results and initiate a discussion. A total of sixty children took part in this study, with 35 diagnosed with ASD and 35 TD children. The demographic information for both the ASD and TD groups is outlined in Table I. Notably, both groups exhibited a similar mean age, with ASD children having a mean age of 8.10 and TD children having a mean age of 9.40. However, the age variation was slightly wider among TD children, ranging from 6.30 to 11.06 years, compared to ASD children, whose ages ranged from 6.30 to 10.50 years. Correspondingly, TD children had a higher mean height and weight compared to ASD children, with mean heights of 128.5 cm and 124.7 cm and mean weights of 30 kg and 28.8 kg, respectively. The range of heights for TD children was more extensive, spanning from 95 cm to 159.5 cm, resulting in a higher standard deviation (SD) of 18.07, compared to ASD children's SD of 13.26. However, the weight variation among both ASD and TD children exhibited a comparable pattern, with standard deviation (SD) values of 11.14 and 11.60, respectively. It is noteworthy to mention that a substantial proportion of the ASD subjects approached by the researcher were boys, as depicted in Fig. 5. Approximately 60% of the ASD children involved in this study were male. This observation may be attributed to the fact that diagnosing autism in boys is often more straightforward than in girls. This finding aligns with previous research, which has consistently shown that ASD is nearly five times more common in boys than in girls [38].

The outcomes of the Mann-Whitney test unveiled noteworthy distinctions ($p < 0.05$) in muscle activation between these two cohorts of children, as succinctly outlined in Table II. Specifically, five muscles were found to be significantly useful in distinguishing between 'Normal' and 'Autism' categories. The p-value for the TA (30%) muscle was found to be 0.017, whereas for the BB the corresponding p-values were 0.021 (10%) and 0.018 (80%), respectively. Meanwhile, the GAS muscle displayed p-values of 0.049 (50%) and 0.034 (60%) respectively. Drawing from the results detailed in Table II, it can be deduced that there exist notable distinctions (highlighted in gray) in the activation of lower limb and arm muscles between ASD and TD children during walking, particularly in the TA, GAS, and BB muscles.

TABLE I. SUBJECTS DEMOGRAPHIC DATA

Subjects	Age (years)		Height (cm)		Weight (kg)	
	Ave	SD	Ave	SD	Ave	SD
ASD	8.10	2.20	124.5	13.26	27.5	11.14
TD	9.40	2.67	128.5	18.07	30.0	11.60

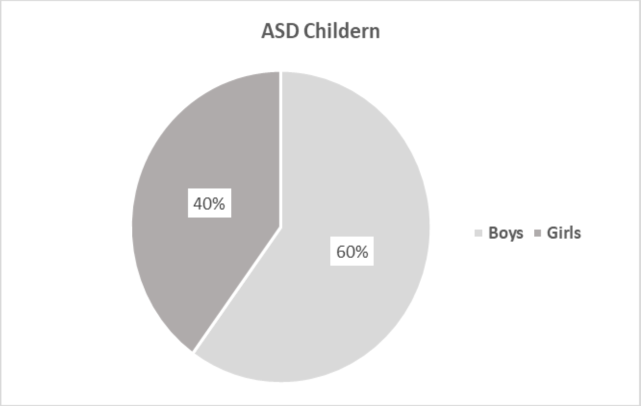

Fig. 5. Gender data for ASD children.

TABLE II. RESULTS FROM MANN-WHITNEY TEST

Gait Cycle	LR 10%	MST 30%	TST 50%	PSW 60%	ISW 80%	MSW 90%	TSW 100%
BF	0.688	0.494	0.495	0.441	0.415	0.321	0.54
RF	0.925	0.803	0.75	1.001	0.651	0.635	0.232
TA	0.974	0.017	0.273	0.534	0.477	0.852	0.69
GAS	0.136	0.162	0.048	0.033	0.305	0.182	0.52
BB	0.02	0.401	0.173	0.864	0.002	0.83	0.491
TB	0.475	0.277	0.964	0.858	0.573	0.682	0.284

The performance of the ANN classifier was assessed using a confusion matrix, as depicted in Table III. The confusion matrix reveals that out of the ASD children group, 3 data points were accurately classified as belonging to the ASD group, and 5 data points from the TD children group were correctly classified as TD. However, there were 3 instances where data from the ASD children group were erroneously classified as TD children, and only 1 data point from the TD children group was incorrectly categorized as ASD children. The accuracy of the SCG ANN classifier is calculated at 66.7%. Additionally, the classifier exhibited a specificity of 91.7%, sensitivity of 79.2%, and precision of 90.5%.

The performance of the SCG ANN classification model was calculated based on the disparity between the actual and predicted gait parameters derived from the EMG signal data. As illustrated in Fig. 6, the x-axis denotes the number of hidden neurons, while the y-axis represents the MSE values. The highest error was observed with four hidden neurons, resulting in an MSE value of 0.9482. In contrast, the lowest error was achieved when using 10 hidden neurons, yielding an MSE value of 0.1542. Notably, in this study, the SCG ANN system with 10 hidden neurons exhibited the most favorable performance among the classification model algorithms. The distribution of error within a neural network serves as a valuable area for exploration and is recommended for determining improved neural network performance criteria and addressing conflicting classification results [39].

TABLE III. CONFUSION MATRIX FOR SCG ANN CLASSIFICATION MODEL

	Positive	Negative
Positive	3 (TP)	1 (FN)
Negative	3 (FP)	5 (TN)

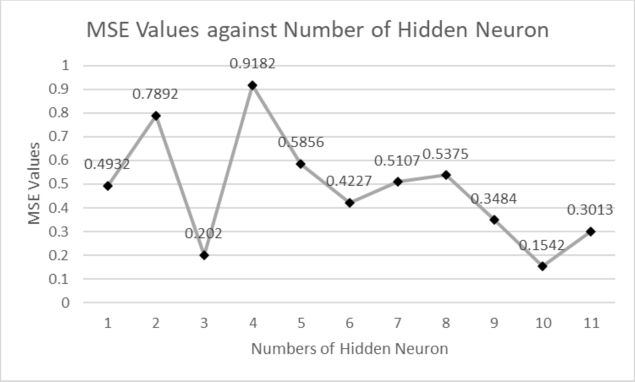

Fig. 6. MSE value in testing performance.

TABLE IV. CONFUSION MATRIX FOR SVM CLASSIFICATION MODEL

	Positive	Negative
Positive	7 (TP)	2 (FN)
Negative	1 (FP)	2 (TN)

The performance of the SVM classifier was assessed using a confusion matrix, as presented in Table IV. The confusion matrix indicates that 7 data points from the ASD children group were accurately classified as belonging to the ASD group, and 2 data points from the TD children group were correctly classified as TD. However, 1 data point from the ASD group was erroneously classified as TD, and 2 data points from the TD group were incorrectly categorized as ASD. With an accuracy of 75%, the SVM classifier demonstrates robust classification capabilities for distinguishing between ASD and TD children. Additionally, the classifier exhibited a specificity of 50%, sensitivity of 87.5%, and precision of 78%.

Fig. 7 provides a comparison of the performance measures of the SCG ANN and SVM classifiers. Notably, the ANN classifier outperformed the SVM classifier in terms of precision and specificity, achieving values of 90.5% and 91.7%, respectively. Conversely, the SVM classifier surpassed the SCG ANN classifier in terms of accuracy and sensitivity, with values of 75% and 87.5%, respectively. It is worth mentioning that specificity is particularly valuable when interpreting positive test results to estimate an individual's probability of having a disease [40]. Overall, both developed classifiers demonstrated impressive performance with consistent rates of accuracy, sensitivity, specificity, and precision.

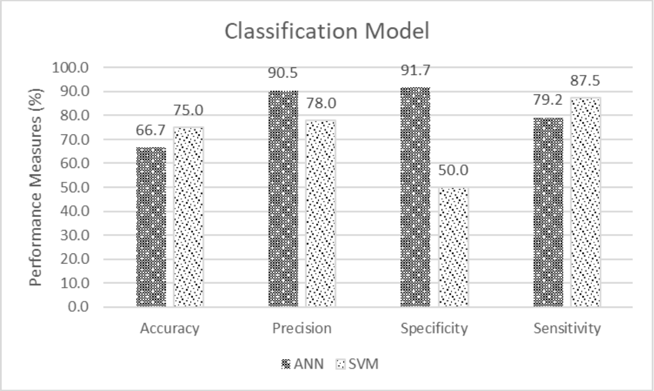

Fig. 7. Comparison of performance measures for ANN and SVM classifier.

As previously mentioned, the primary objective of this investigation was to categorize ASD and TD children by analyzing EMG signals recorded during walking. Despite its inherent challenges, the analysis of EMG data provides valuable insights into diagnosing ASD children through the assessment of muscle activation during walking. In the initial phase of the study, a database of EMG signals for both ASD and TD children during walking was established through the data collection process. The Mann-Whitney test, with a 95% confidence interval, was utilized to scrutinize significant differences in muscle activation among BF, RF, TA, GAS, BB, and TB muscles in both groups of children. The analysis of EMG signals has emerged as a promising diagnostic approach for identifying autism based on muscle activation patterns during walking.

The subtle motor deficits in individuals with autism can manifest as abnormal gait patterns, with variations in muscle extension being a contributing factor [41]. Difficulties in walking among children with ASD may arise due to heightened variability in velocity and the manifestation of irregularities in stride length and duration [42]. Additionally, a study by [43] demonstrated that movement disorders were observable in ASD children, characterized by irregular steps and vigilant gait during normal walking, as observed in video recordings during experiments. This study has revealed that three muscles—TA, GAS, and BB—were affected during walking in ASD children. The TA muscle, in particular, showed significant activation differences between ASD and TD children [44]. This discovery aligns with earlier research indicating that body movement and arm swing during walking can amplify TA muscle activity [45].

Similarly, while the walking patterns of ASD children may appear relatively normal on the surface, many of them exhibit subtle gait abnormalities that can impact lower limb muscle activation [41]. The BB muscle exhibited significant disparities between ASD and TD children during walking, likely attributable to its role as a primary mover during the concentric phase [45]. Consequently, the BB muscle in ASD children was notably affected and distinct from that in TD children during walking. These results substantiate the study's hypothesis, which proposed that EMG data from ASD children during walking could be precisely classified using SCG ANN and SVM classifiers.

As far as we are aware, our study constitutes the initial exploration into the classification of ASD and TD children based on muscle activation in both lower limb and arm muscles during walking. The results demonstrate that the proposed method successfully classifies ASD and TD children, with high accuracy, specificity, sensitivity, and precision. This research has significant implications for both rehabilitation and clinical applications. The experimental results validate the accomplishment of the study's objectives, and the selected parameters for investigating gait in ASD children during walking have been validated by previous researchers.

The developed classification model system exhibits robust performance, achieving high accuracy rates, specificity, sensitivity, and precision. While this study has succeeded in classifying ASD and TD children, future research may consider classifying the severity of ASD conditions, as suggested by [46]. Additionally, expanding the sample size of ASD participants could further validate the EMG signal patterns observed in this study.

IV. Conclusion

In conclusion, this study has revealed significant differences in muscle activation patterns in the lower limbs and arms of individuals with ASD during walking, focusing on muscles including BF, RF, TA, GAS, BB, and TB. Notably, the TA, GAS, and BB muscles exhibited distinctive features between ASD and typically developing individuals. Two classification models, SCG ANN and SVM, were then introduced to discern these features from the EMG signals. Following classifier training, the SVM model emerged as particularly promising for distinguishing between ASD and TD children. These findings underscore the significant characteristics present in EMG signals between ASD and TD individuals, affirming the efficacy of classification model algorithms in differentiation. This discovery holds substantial potential for automating ASD screening and diagnosis, facilitating the design of more effective treatments and rehabilitation strategies by parents and therapists, thus advancing precision health.

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Improving Load Balance in Fog Nodes by Reinforcement Learning Algorithm

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***Abstract*—Fog computing is a distributed computing concept that brings cloud services out to the network's edge. Real-time user queries and data streams are processed by cloud nodes. Tasks should be evenly divided among fog nodes in order to maximize speed and efficiency, optimize resource efficiency, and reaction time. Real-time user requests and data flow processing are done by cloud nodes. Nodes in a network must share responsibilities in a balanced manner in order to maximize speed and efficiency, resource efficiency, and reaction time, hence in this article, a novel approach is presented. When it comes to fog computing, load balancing essential suggested to be improved. According to the suggested algorithm, a task submitted to the fog node via a mobile device would be processed by the fog node using reinforcement learning before being passed on to another fog node. Neighbor or let the cloud handle it. According to the simulation findings, the suggested algorithm has achieved a reduced execution time than other compared approaches by properly allocating the work among the nodes. Consequently, the suggested technique has reduced the chance of incorrect job assignment by 24.02% and the response time to the user by 31.60% when compared to similar methods.**

Keywords—Fog computing; resource allocation; reinforcement learning; delay; load balancing; fog nodes

I. Introduction

Load balancing is a fundamental concept utilized in cloud settings for allocating computing resources among servers and devices [1]. By balancing the use of hardware, network, and software resources, load balancing aims to maximize system performance, increase efficiency, and provide the best possible user experience [2]. Reinforcement learning algorithms are an artificial intelligence approach to load balancing that provides automatic and adaptive performance enhancement [3]. IoT devices usually assign task processing to the nearest fog node. In this case, it's possible that certain fog nodes take on more tasks than others and eventually become overburdened. In order to avoid this, load balancing techniques are used to spread tasks among fog nodes equitably [4]. Fog nodes are distributed throughout the environment [5]. Two distinct forms of load balancing are utilized in dispersed environments: static load balancing and dynamic load balancing. When choosing a load balancer, static load balancing ignores the target fog node's state [6]. On the other hand, dynamic load balancing chooses which fog node to route traffic based on its present status [7]. Dynamic load balancing is applied in this post. Load balancing among fog nodes reduces expenses, latency, and user response times while simultaneously enhancing resource productivity, efficiency, resource conservation, and real-time event detection [8]. Numerous load balancing techniques have been presented recently, and they are all effective in certain system situations. Meta-heuristic or hybrid load balancing algorithms may be taken into consideration, depending on the approach used [9]. There are two types of heuristic algorithms: static and dynamic. Initiatives entail limitations intended to determine the best course of action for a certain problem [10]. These algorithms have an advantage over meta-heuristic algorithms in that they are easily implemented and yield good results. Meta-heuristics require finality because of the enormous immensity of their solution space and the fact that they are completely random processes [11]. The type of problem, how it was initially set up, and the strategy employed to find a solution all have a big impact on how long it takes to resolve. In terms of execution time and cost, coupled algorithms—which are produced by combining numerous meta-heuristic heuristic algorithms—are more efficient than other algorithms [12]. Through the use of reinforcement learning techniques, the fog system can automatically and dynamically adapt to changes in compute load and service requirements [13]. Based on an assessment of the present status of the system and clients, the fog system can determine whether to add or subtract computing resources from a server, shift load from busy servers to freer servers, or assign resources to services and requests according to their importance. The system will be able to use the greatest computing resources and adapt dynamically to the different needs of users and services by employing this technique, which will significantly improve load balancing in fog computing.

Due to the distributed nature and dynamics of fog computing, however, conventional load balancing techniques become less effective, necessitating the development of an algorithm that can change with the context through time. To achieve this goal, a decision-making procedure based on reinforcement learning is suggested in this article to locate sparse fog nodes [14].

The agent chooses the right fog node based on the experiences it obtains from the environment in each scenario, which makes the proposed technique, the delay may be greatly reduced. Additional and time-consuming calculations are also removed in the proposed method of this article. Reinforcement learning for load balancing is superior to conventional approaches in that it not only simplifies the algorithm framework without taking any network model assumptions into account, but also converges to the best policy in polynomial time. The collected findings demonstrate that, when compared to the compared approaches, the suggested load balancing method greatly decreases the lag and reaction time to the consumer. This article's conclusion is structured so that it is discussed in the section of current related research in the area of load balancing in fog computing.

Section III explains the concept of the proposed system, the reinforcement learning technique, and how to find the system's delay. The suggested load balancing strategy is presented in Section IV. The evaluation and comparison of the simulation results with earlier techniques are done in Section V. Section VI will conclude with recommendations for additional research.

II. Related Work

In fog computing, jobs are typically assigned to the nearest fog node by mobile users and IoTs devices. These devices are frequently mobile, therefore depending on where they are in the network, various important nodes may have varying loads. Due to this problem, some fog nodes may be overburdened while others may be idle or underloaded in terms of the distribution of work. Methods to solve the load balancing issue in the fog computing environment have been presented by some authors. These actions can be divided into various categories [15].

Here, prior research on task delegation in which nodes need to be aware of each other's computational capabilities will be examined. To discover the best loading decision in the presence of an uncertain reward model and transition probability, [16]. According to the resource capacity, fog nodes in the presented process can assign an ideal number of incoming jobs to a free neighboring fog node. This is done to cut down on processing time and potential overhead [17]. They looked into load balancing on several kinds of computing nodes before officially presenting the fog computing system's structure. Then, they developed a matching resource allocation strategy for fog environments, which combines static resource allocation with dynamic service transfer, to accomplish load balancing in fog computing systems. The min-min method was developed by [18] to take network resources into account. When sending a job to a cluster node that is overloaded, factors such the distance between the cluster and the node next to it, the amount of tasks that are waiting in each cluster's queue, and the distance between the cluster node and the closest cloud data center are taken into account. Researchers suggested the min-min method in [19] and put it into practice inside each cluster while taking network resources into account. In this method, a neural network is used to evaluate the fog node's current capacity. The Internet of Things gadget transmits its work to the cloud if it doesn't get the necessary resource. In this study, a four-layer architecture for load balancing and task scheduling is proposed. The Internet of Things is a component of the top layer, where a lot of data is generated and sent at once. The jobs are divided into two categories important and less important in the second layer via a dual fuzzy logic method. The user-proximate nodes with the lowest load are given priority for task execution [20].

Other works are predicated on the knowledge of the node's load or the prediction of its future load. This algorithm continuously gathers network traffic, server load information, and control information. By merging fog computing and software-based networks, [21] devised a load balancing technique based on reinforcement learning. In order to offer the greatest amount of access to the resources, this algorithm analyzes the behavior of the network and divides up the work by considering network's current load and forecasting its future load. The network is adaptable thanks to this architecture's dispersed nature. In this article, a threshold limit is taken into consideration to implement the load balancing method, and if the server load exceeds 75%, the load balancing algorithm is called. In order to achieve better load balance, [22]. It also applies reinforcement learning to handle the task loading problem. In this study, Deep Q-Learning is enhanced using an LSTM network. The quantity of input data needed for the sub-task, the downlink bandwidth, the amount of output data generated by the sub-task, and the load on each server make up the state space in this article. The action space is a vector with m + 2 zero- and one-dimensional dimensions. A cloud server and a mobile device are included in the m and 2 edge servers. Any of the same folders can be used to download data to the server. The three variables of load balance, cost, and energy consumption are taken into account by the reward function. In study [23], Berardi and colleagues address the issue of resource management by presenting two distributed load balancing algorithms, Sequential Forwarding and Adaptive Forwarding, which are intended to handle heterogeneity. They do this by assigning jobs to nearby nodes. According to the threshold limit and the maximum number of steps, M, a task is delivered at random to nearby fog nodes using the first approach, known as the Sequential Forwarding method, until it reaches the correct node. The second method, known as the Adaptive Forwarding method, is suggested since it is difficult to define the working parameters and M. This method automatically and conditionally updates these parameters. For a fog computing environment, the research in [24] presented a load balancing method that works well for medical applications.

The techniques described in earlier studies demonstrate that the majority of these techniques require knowledge about the nodes' capacity or load in order to make decisions [25]. This effort necessitates a number of time-consuming computations that add latency and raise network traffic burden shall be. Additionally, in the majority of these approaches, the load balancing operation and load distribution are often performed by a single node. In contrast to other works, this one uses a different decision-making procedure because, according to the suggested method, the fog node decides on processing and task assignment only after gathering information from the delay and reward during the learning period and after taking into account its own capacity and the positions of other nodes [26]. The proposed solution is intended to address a subset of difficulties, although its use is not constrained to a particular scenario. Additionally, the strategy suggested in this article is dynamic and adapts to the circumstances of the agent's goals.

III. System Model

The description of the suggested system and the reinforcement learning algorithm will be covered first in this part. The load balancing problem formulations are then provided using reinforcement learning.

A. System Description

The paper takes into account a four-layer design for the suggested system, which includes Internet of Things, fog nodes, proxy servers, and cloud data centers, as shown in Fig. 1. The Internet of Things layer, which contains various end devices including wireless sensor nodes, mobile devices, etc., is the initial layer in this system. These gadgets can transmit data to nearby fog nodes because they are directly connected to them. The fog layer, which is the second layer, is made up of extremely intelligent equipment like routers, switches, and gateways that take in and process data from endpoints [27]. The cloud data center layer, which consists of numerous computers and data centers, is the fourth tier. This structure eliminates the requirement for data transfers to the central cloud by allowing data and information processing to take place locally in fog nodes [28]. Due of their limited computational power, mobile devices in the proposed system assign fog nodes within their range to process a portion of the work (a virtual reality game). Since there is no master node or controller in this system that keeps track of the fog nodes' status and the external conditions, it is up to the fog nodes to collect data and make decisions [29], [30].

The proposed system operates as follows: On the user's smartphone, an Android application called Tractor Beam2EEG (a type of game where players compete against each other) is running. This application demonstrates how the human brain and the computer interact. Each player must have a headset attached to his smartphone in order to play this game. This application continuously monitors the signals picked up by the headset, the processing, and the mental state of the user. Processing the software can need a lot of processing power. Therefore, in this article, the program is broken into multiple pieces known as subtask 3 in order to enhance the processing time, transfer time, and boost the usage rate of network resources. The following dependencies, depending on virtual reality game tasks, are presented in this article. The software is divided into five subtasks, as illustrated in Fig. 2: EEG, Client, Actuator, Concentration-Calculator, and Connector. These subtasks' data are interdependent.

The major processing modules in this application are the Client, Concentration-Calculator, and Connector modules. In order to receive the EEG signals, the Client module interfaces with the sensor. Once it has received the signals, it checks their levels and, if they are constant, passes them to the Concentration module. Calculator that assesses the user's mental state based on the signal it receives and computes their level of concentration [31]. The Client module is then informed of the computed concentration level by the Concentration-Calculator module. The Connector module connects the game amongst several participants who may be present in geographically dispersed areas by operating on a global scale. The Client module of each connected user receives a constant stream of information from the Connector about the game's current condition [32]. Numerous modules can be kept on mobile devices due to the fact that these sub-tasks require less computational complexity and data transfer, while those that demand greater computing resources can be assigned to the cloud provider's nodes. The loop that transforms the user's mental state into the game's state on the mobile device's screen is the most crucial control loop in this application. The mobile device and the device that houses the user's brain state calculation module must communicate in real-time for this to work. The user experience is significantly impacted by latency in this loop because it affects the entities that the user interacts with directly [33].

The computing modules should be as near the data sources as possible to minimize the latency in data transmission between units. The EEG, Client, and Actuator modules of this article's suggested design, as illustrated in Fig. 3, are connected to mobile devices. Each module in the loop processes the program, forwarding the processed data to the subsequent module, and so on, until the Actuator module in the mobile device receives the program's final results [34]. Each fog node has an unpredictable amount of mobile devices connected to it at any one time given time due to the dynamics of the environment, and it is possible that some fog nodes acquire more subtasks than others and eventually become overloaded. To prevent this, fog nodes are evenly divided into sub-tasks using load balancing techniques.

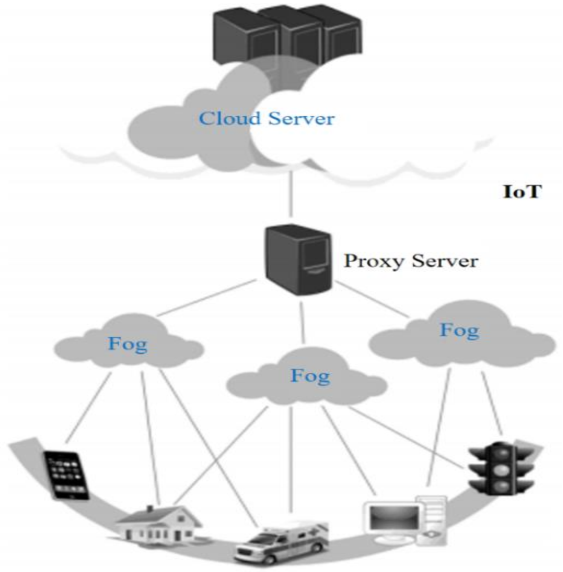

Fig. 1. Architecture of fog computing layers.

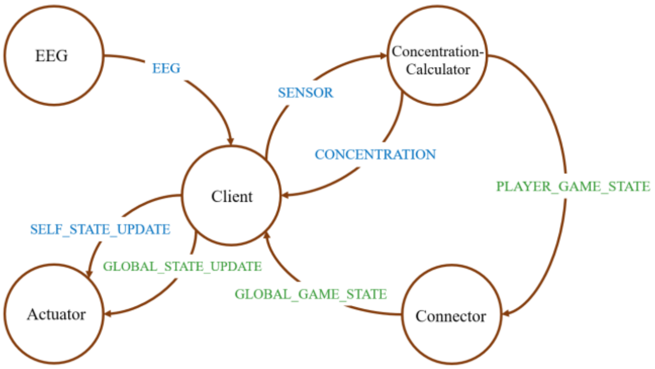

Fig. 2. Subtasks and their dependencies.

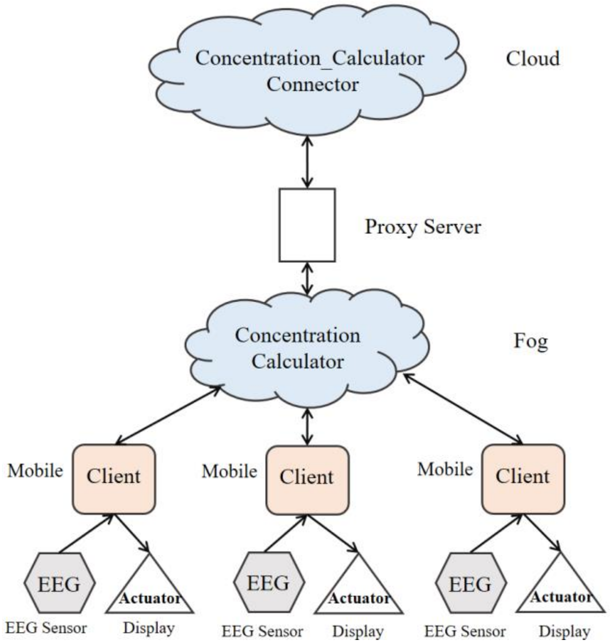

Fig. 3. Module placement in various devices.

The load balancing algorithm's primary goal in a fog computing setting is to increase the user reaction time by dispersing the system's total load so that it can continue to operate at its best under dynamic system settings. This article's goal is to reduce network resource loss, user response time, and delay by applying the reinforcement learning method to the fog nodes. When a fog node receives a subtask, it employs a reinforcement learning algorithm to decide whether to process it independently, pass it on to another node in the area, or send it to the cloud to be processed faster.

B. *Reinforcement Learning Algorithm*

Supervised, unsupervised, semi-supervised, and reinforcement learning are the four main types of machine learning algorithms. Numerous labeled input data are needed for supervised learning in order to train the system. Unsupervised learning, as contrast to supervised learning, involves learning from unlabeled events in order to uncover hidden patterns in the data. Unlabeled data and labeled data are used in supervised fog learning to increase learning accuracy [35]. The agent can learn the best actions from the environment through reinforcement learning. Through environment exploration, trial and error, and use of the incentives provided by the environment, this learning is accomplished [36]. In this article, load balancing is accomplished by Q-L algorithm. The proposed approach formulates the load balancing problem as a Markov decision process (MDP), where the fog node takes a decision after learning the state of its surroundings and is rewarded by it. Experience is the end result of trial and error and is characterized by the four states of the present state, action, reward, and next state [37].

1) Policy: The agent's behavior can take one of two forms when it comes to policy: active policy, in which the agent learns the value function in accordance with the performance that the current policy has caused, or passive policy, in which the agent learns in accordance with the action that the policy has caused [38]. The function learns the value, the other is obtained, and it is defined. The Q-Learning algorithm is a passive algorithm with a greedy learning strategy for the Q value.

2) Value function: The learner function's reward function sets the objective, and the closer it gets to the target, the more reward it receives. The value function in reinforcement learning, on the other hand, derives a value as Eq. (1) for each state and has a long-term perspective. The closer to the objective this value is, the higher it is.

$$v*(s) = max \sum_{s',r} p(s',r|s,a)[r + \gamma v*(s')] \quad (1)$$

The discount factor, often known as $0 < \gamma < 1$, in this context determines the significance of potential benefits in the future and the decision made right now is more important than those made in the future.

In states, the agent takes action (A) to change the environment from its present state to a new state (b) and receives a reward (r) for his efforts; both factors influence his future decision-making.

3) Model: The reinforcement learning problem has a random model with non-deterministic states. Going from one state to another and taking any action are both possibilities [39].

Reinforcement learning has thus found various uses in optimization in the dynamic, unpredictable, and changing environments of fog and clouds. Additionally, it might be a good way to evenly distribute loads among fog nodes [40].

C. *Formulation of the Problem*

Discrete time stochastic control is what the MDP is. One method for solving MDP is reinforcement learning, which in turn makes use of dynamic programming. To achieve the target performance, the suggested load balancing problem is expressed as an MDP. For the suggested load balancing problem, the fours $< S, A, P, R >$ are defined below, which are typically included in MDP:

1) The state space $S = \{s\,(C, Q, N)\}$ represents the relationship between the fog node's capacity (C), the size of its upstream queue (Q), and the number of mobile devices (N) linked to the fog node.

The Q-L algorithm bases decisions on the system's present state. Many of the earlier techniques for defining the state space call for knowledge of the nearby nodes' capacity [41]. However, the state of the system is solely specified in the proposed method based on the state of the decision-making fog node, which forces decisions to be taken without knowledge of the states of the surrounding nodes.

2) In the action space $A = \{a = (n)\}$, n represents the choice of a fog or cloud node to be assigned to the subtask.

3) P: A number between zero and one represents the transition probability. In order to be in state s, the criterion is to have the probability distribution of the transition $P(s'|s, a)$ to the next state s', with the action choice.

4) R: The state's activity is directly linked to the reward. The primary objective is to minimize processing delay and overhead probability while maximizing long-term value in each system by selecting the appropriate action.

As was already noted, there are various subtasks within the task (virtual reality game). The sum of all linked sub-tasks' transmission and processing delays across all relevant devices is the task execution delay and is determined as follows:

$$T_{task} = t_{uot} - t_{in} \tag{2}$$

where, $t_{out} and\ t_{in}$ represent, respectively, the entry time and exit time of a task in the suggested system. Since the processing and transmission delays in mobile devices are relatively constant, this article solely calculates the processing delays of the Concentration-Calculator subtask in fog or cloud nodes and the subtask in the mobile device to compute the delay of task execution [42]. It is seen as having a constant value. The suggested method uses fog nodes to perform the Q-Learning algorithm, Additionally, the subtask's processing delay is equal to the negative of the reward function (R $R(s,a)$), which is allocated to the fog node. The longer the processing delay of the subtask, the better. As a result, $R(s,a)$ will be lower than expected. The calculation looks like this.

$$R(s,a) = -T_{Subtask} \tag{3}$$

This refers to the calculation subtask that the fog node is tasked with performing, where $T_{Subtask}$ is its processing delay. The symbols used to evaluate the system and the delay calculation formulas are listed in Table I.

TABLE I. SYMBOLS USED TO EVALUATE THE SYSTEM AND DELAY CALCULATION FORMULA

Parameters	Description	Value
W	How many smaller jobs ran on the node	-
L	Subtask data size	3500
B	Bandwidth per node	10000
$d_{i,j}$	How far apart are the nodes i and j?	-
β_1	Path loss constant between two nodes	10^{-3}
β_2	path loss power	5
P	Power transfer between nodes	20 dBm
N_0	Spectral density of noise power	175 dBm /Hz
I	Quantity of subtask-specific commands	200×10^{6}
Cycle	The amount of CPU cycles used by each instruction	5
f	Fog node cpu speed, cloud cpu speed	2800 44800
N	Just how many fog nodes	4
n	The frequency with which a state is displayed	-
α	Rate of learning	2/n
y	reduction element	0.8

The subtask's processing lag depends on whether its processing is done in the fog the node that the mobile device sent the subtask to $(FN-I)$ or whether it is handed over to the neighboring fog node $(FN-J)$ or the cloud.

- The following formula determines the execution delay of the subtask, which is equal to Subtask if the subtask is processed by $FN-I$.

$$T_{Subtask} = \frac{I\times Cycle\times W}{f} \tag{4}$$

- If the subtask is delegated to $FN-I$ or Cloud for processing, $T_{Subtask}$ is calculated as follows.

$$T_{subtask} = t_{W_i} + t_{c_{ij}} + t_{E_j} + t_{W_j} + t_{c_{ji}} \tag{5}$$

In this regard, t_{W_i} and t_{W_j} are the waiting delay of the subtask in the I-FN sending queue t and the J-FN sending queue or cloud is affected by the subtask's waiting delay. $t_{c_{ij}}$ denotes the time it takes for the subtask to be transmitted over the communication channel. Moving from I-FN to J-FN or the cloud. The subtask execution delay in J-FN or the cloud is represented by t_{E_j}, whereas the subtask result delay from J-FN or the cloud to I-FN is represented by $t_{c_{ij}}$. A node's (i) or cloud node's (j) waiting delay in the sending queue is determined in the following way.

$$t_w = t_o + t_i \tag{6}$$

where, t_o and t_i are respectively the entry Add the arrival time of subtask m to the node's queue and record the departure time of subtask m from the same queue. The latency of subtask transmission on the communication route between FN-I and FN-J or the cloud, and vice versa, is equivalent to:

$$t_c = \frac{L}{r_{i,j}} \tag{7}$$

where, $r_{i,j}$ The transmission rate between nodes i and j is denoted as.

$$r_{i,j} = Blog(1 + \frac{g_{i,j}\times p}{B\times N}) \tag{8}$$

where, $g_{i,j} = \beta_1 d_{i,j}^{-\beta_2}$ is the gain of the channel between two nodes i and j. The delay of execution of the subtask in J-FN or cloud t_{E_j} is equal to:

$$t_{E_j} = \frac{I \times Cycle \times W}{f} \qquad (9)$$

Each fog node is a learning agent operating in an S-state space environment. Each time a new task is added to the system, the agent performs an action in the surrounding area and chooses one of the nodes to receive the new work. In the event that the environment state is updated, the reward for this allocation will be decided. The agent will receive the reward if the system is now operating with a load balance that is closer to ideal and the subtasks are processed more quickly than they would otherwise [43]. Each node progressively acquires the ability to optimize its decision-making process for handling subtasks based on the rewards it receives. Minimizing the delay of sub-task processing in the fog environment will reduce the overall delay and response time to the user, resulting in the network spending less time on task processing.

IV. The Proposed Load Balancing Method

In order to address the issues with the prior approaches, the load balancing algorithm based on reinforcement learning is presented in this section. It is designed to distribute the load uniformly among the intermediate nodes of the fog. Dynamic programming can solve MDP when the system for every state-action combination has a transition function and a reward function, but typically the system is unable to anticipate the precise value of the transition function and reward for the majority of the states, which is required to solve the problem. It is suggested to use reinforcement learning to solve these issues. The Q-Learning algorithm, one of the reinforcement learning algorithms, is utilized in this article to locate the ideal action mode with the least amount of computing expense, making up for the absence of appropriate data through experimentation. The Q-Learning algorithm's model is a random model.

Distributes an agent involved in network learning is referred to as a fog node. The sub-fog node will choose to use reinforcement learning to process a new task after receiving it. Hence, the fog node designated for the Concentration-Calculator task acquires data from the mobile device. The fog node then assesses the environment and, in order to maximize the long-term reward, decides whether to complete the subtask independently or to delegate it to a nearby fog node for quicker completion based on its capacity and past experiences and rewards. If the Concentration-Calculator subtask takes longer to process in the fog nodes than it does in the cloud, the fog node chooses to transfer this subtask's processing to the cloud, which will speed up processing and lighten the load on the fog nodes. According to the system model, each fog node performs a response after observing the current states, a delay is made, and the new state s' is observed, and for that, it receives a reward (R, s, c) from the environment.

$$Q_{new}(s,a) = Q_{old}(s,a) + a[R(s,a) + \gamma \max_{a} Q(s',a') - Q_{old}(s,a)] \qquad (10)$$

The learning rate, 0 $1 < \alpha < 1$, strikes a balance between previously learned material and new observations. Using the available knowledge, the greedy method selects a course of action that yields the greatest reward in a single step. The Learning-Q method uses the likelihood of selecting an action ε, where ε –greedy is the policy with larger reward, in order to maximize the long-term value. The fog node is chosen to complete the subtask in order to maximize long-term value. In this manner, a random action with a fixed probability ε –greedy is chosen in each time step of the algorithm $0 \leq \varepsilon \leq 1$.

The benefit of utilizing 1–ε and the action with the highest value is that as the number of steps rises, every ε –greedy of the Q(s,a) algorithm exhibits an infinite action, ensuring that it will eventually converge to the best value. As a result, using the Learning-Q method, the fog node learns to choose the best node for handling the subtask. The suggested method calculates the suitable reward function using 3.

Since the function of infinity has been observed, it is certain that (Q, s, and a) will eventually converge to the ideal value. Consequently, using the Q-Learning method, the fog node learns to choose the best node for processing subtasks. The load balancing solution that has been suggested calculation of the suitable reward function is shown in Fig. 4 and it is done using Eq. (3). The fog node learns the complete network and the likelihood of loading to each node as it traverses the network using the learning method, enabling it to select the best node to transfer the task to. The algorithm begins by using a greedy approach to explore the network, and once it has a thorough understanding of the network's requirements, it performs optimal load balancing. The state space encompasses the capacity of the fog node, the length of the uplink queue within the fog node, and the quantity of mobile devices linked to the fog node. In order to minimize the processing delay for the subtask, select either a reward eyebrow or a fog node.

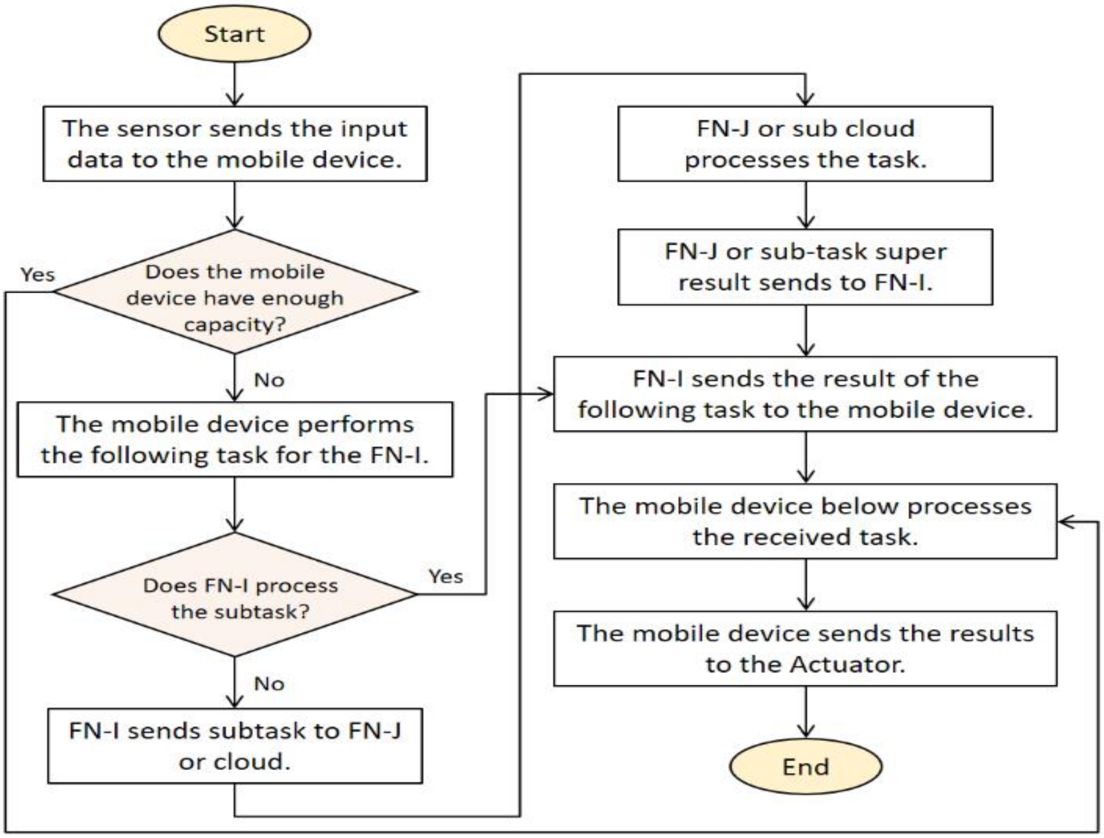
Start
The sensor sends the input data to the mobile device.
Does the mobile device have enough capacity?
Yes
No
The mobile device performs the following task for the FN-I.
Does FN-I process the subtask?
Yes
No
FN-I sends subtask to FN-J or cloud.
FN-J or sub cloud processes the task.
FN-J or sub-task super result sends to FN-I.
FN-I sends the result of the following task to the mobile device.
The mobile device below processes the received task.
The mobile device sends the results to the Actuator.
End

Fig. 4. Block diagram of the implementation steps of the proposed load balancing method.

V. Evaluation and Simulation

This article utilizes the iFogSim simulator [21] to model the load balancing problem using the reinforcement learning technique. This software was executed on a Sous computer equipped with seven Intel Core i processors and eight GB of RAM. The proposed system has N fog nodes and a variable number of mobile devices that establish random connections with neighboring fog nodes to broadcast subtasks. This paper proposes the utilization of the Q-Learning algorithm for load balancing in a fog environment. Initially, the fog node lacks any understanding of the network due to the fact that all the Q-table values in the Q-Learning algorithm are set to zero. The application of the avaricious approach to learning is implemented. Initially, the algorithm conducts an exhaustive search of the network, prioritizing immediate gains, as the number 0 is considered equivalent to 1. Over time, as the fog node's estimation reliability in the Q-table increased, its value changed to 0.3. Additionally, the received reward's value is equal to the concentration-calculator subtask's negative processing delay at the fog or cloud node.

The learning method is applied right away to minimize the generation of overhead in the nodes as it is expected that the task creation and task sending have already been completed in the simulation. The Q-L method allows the fog node to learn the best ways to interact with its surroundings. Through environment exploration, trial and error, and use of the incentives provided by the environment, this learning is accomplished. In general, each fog node assesses the state of the environment, selects a node to assign the work to, and then reaps the benefits. With each iteration of the method, the fog node's network experience grows, and over time it learns to assign the sub-task to a node with a lighter workload and faster processing speed. Contrary to the proposed way, alternative solutions (such as those in sources [6, 8]) conduct the load balancing algorithm before adding overhead to the fog node, which degrades the performance of the aforementioned systems and lengthens their latency. Another benefit is that, in the comparative methods for allocating sub-tasks to surrounding nodes, it is only necessary to be aware of this node's position and capacity, which may be determined by making a few numbers of laborious computations. However, in the suggested system of these computations, time-consuming and redundant tasks are eliminated, and the fog node simply behaves in accordance with the knowledge it has received from its surroundings. By doing this, the proposed system's latency will be as little as possible.

A number of current load balancing techniques have been compared to the performance of the suggested method, and in this simulation, random and proportional SALB load balancing techniques have been employed as benchmarks [6, 8]. The SALB approach examines the adjacent nodes' capacities after the fog node is overloaded and delivers the subtask to the node with the highest capacity and at least 40% of its capacity. Sub-tasks are distributed at random to fog nodes in the random technique. The Proportional approach receives information on each neighbor's capacity and chooses the best node based on the size of the subtask.

Following that, the graphs created by applying the Q-L algorithm to the load balancing problem are provided. Finally, the results of applying all four algorithms are discussed, along with a comparison of how well they performed in terms of delay, user response time, and load balancing.

Fig. 5 displays the progressive augmentation of the cumulative reward with each repetition of the proposed technique. As mentioned earlier, the reward is equivalent to the reciprocal of the processing delay for the subtask assigned to the fog node. The awarded reward will drop as the subtask's processing time increases, depending on whether the cloud provisioning node handles it. The action that yields the highest Q-value is chosen in the decision to transfer the load. According to the effectiveness of the suggested incentive, the proposed technique uses Q-Learning-based load assignment decision to reduce processing duration and overhead likelihood. With an increase in task processing rate, cumulative reward rises. Due to the fact that many tasks are queued up in the nodes, the cumulative reward also continuously falls as the quantity of incoming tasks rises. In this method, the network delay and user response time are decreased as the fog node eventually learns to assign processing of subtasks to the node that causes the least amount of delay.

Fig. 6 demonstrates how the average execution time has decreased dramatically as a result of program repetition and increased learning. In this method, the network delay and user response time are decreased as the fog node figures out which node is the least delay-prone and starts to delegate subtask execution to it. Furthermore, as seen in Fig. 7, the standard deviation of the nodes' load decreases as learning grows.

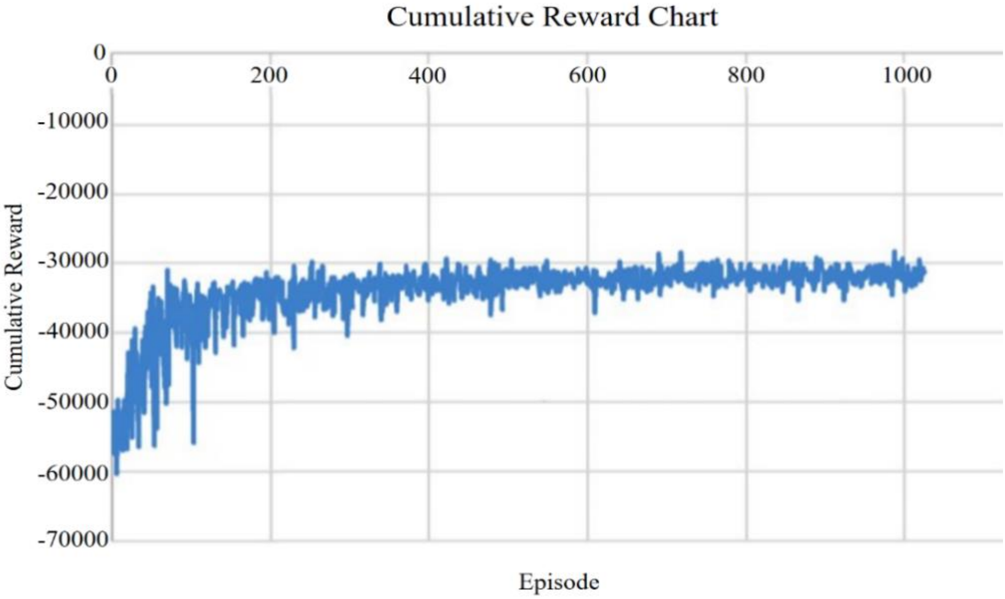

Fig. 5. Increasing payout with each cycle of the suggested method.

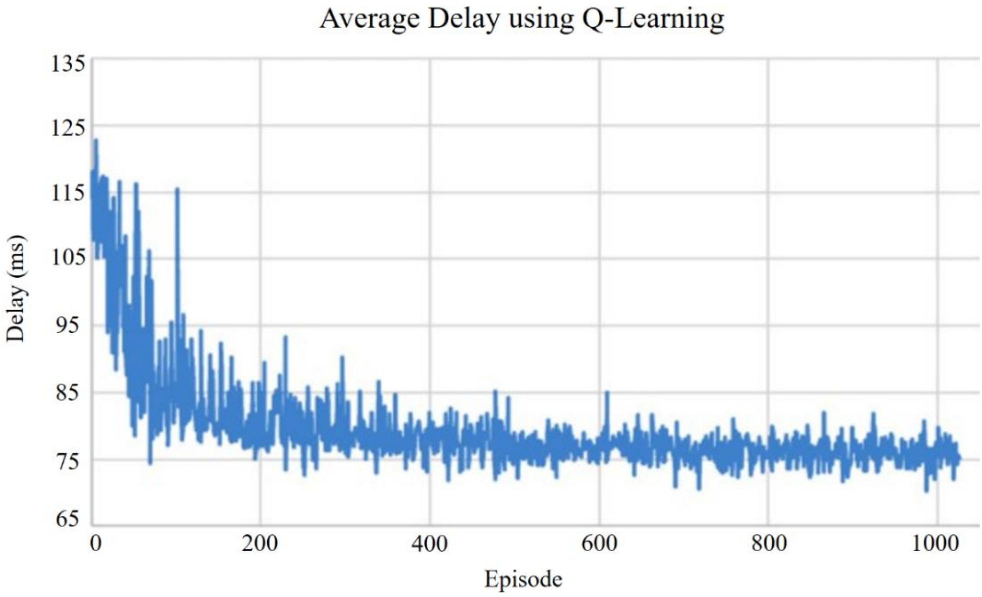

Fig. 6. Average task execution delay in Q-Learning method.

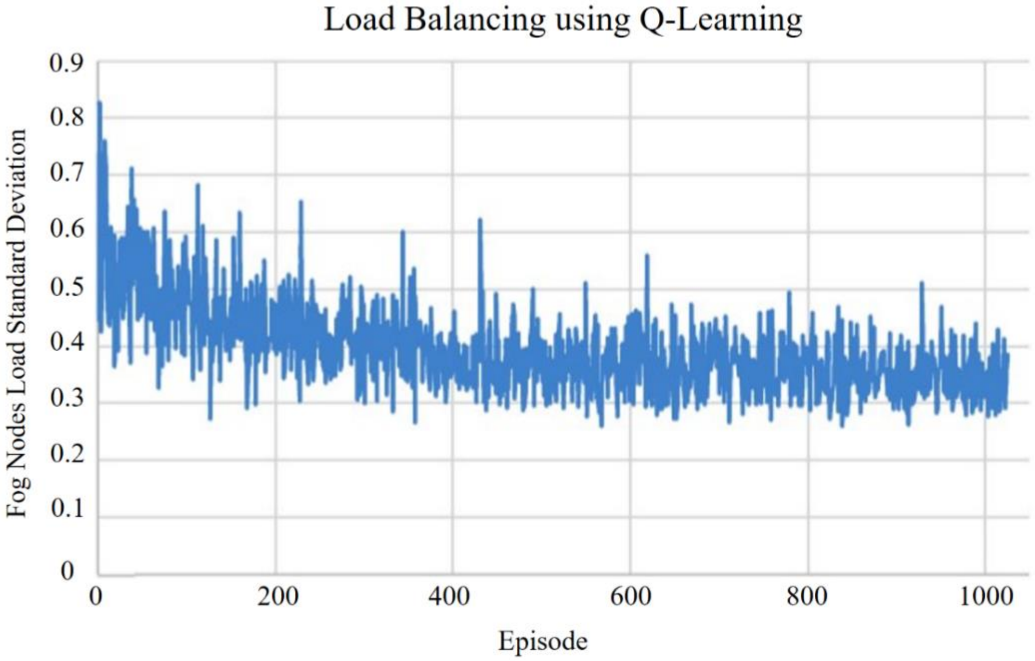

Fig. 7. Standard deviation of load on nodes in Q-Learning algorithm.

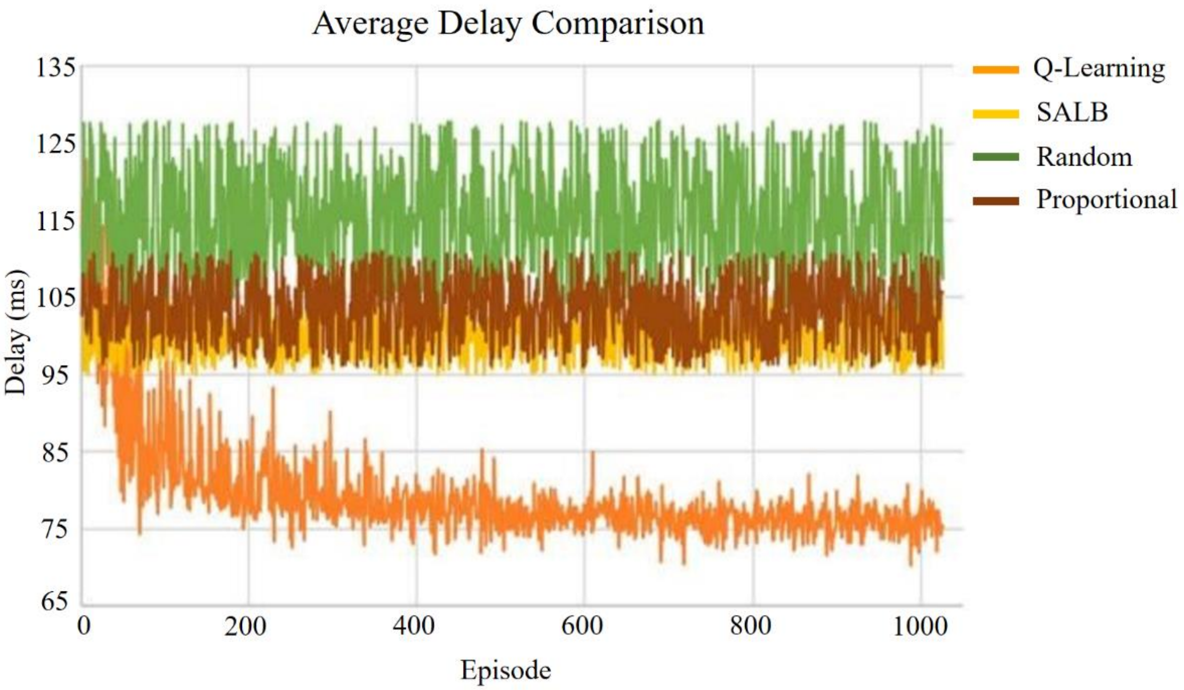

Fig. 8. Average task execution delay.

As a result, the network's job distribution and processing may be guaranteed to be balanced, and load balancing is enhanced. Just as mentioned before, the fog node detects which node causes the least delay and starts sending the subtask processing to that node. If the sub-task is sent to a node with more capacity and can therefore handle the incoming sub-task more quickly, the processing latency of the sub-task is decreased. By giving the subtask to the fog node with the greatest capacity, overhead with minimal strain on other nodes are avoided.

The pressure on the nodes' standard deviation diminishes as learning progresses. As a result, the load balance is enhanced and it is possible to guarantee that the tasks are dispersed and carried out in the network in a balanced manner. As previously noted, the fog node eventually learns to assign the subtask's processing to the node that causes the least delay. If a subtask is assigned to a node that has more capacity and can handle the incoming subtask more quickly, the processing latency is decreased. By giving the work to the fog node with the greatest capacity, overhead and underloading of other nodes are avoided. The outcomes of the execution of all four algorithms are now reviewed, along with a performance comparison. It is anticipated that the Q-Learning algorithm will considerably enhance the network's load balancing capabilities. According to the evaluation's findings, Fig. 8 illustrates how choosing a task based on Q-Learning minimizes task execution latency in accordance with the suggested reward function. The proposed load balancing technique uses reinforcement learning to evenly spread the load across the nodes, enabling the nodes to complete sub-tasks faster.

The cumulative reward drops as the task arrival rate rises because fewer tasks can be processed by fog nodes due to the relatively high amount of subtasks that are queued at them. However, the suggested load balancing method produces a beneficial reward in that the delay is also reduced in the same proportion. This is because the load is distributed properly across the fog nodes. Additionally, unlike the approaches that were examined, no time-consuming computations were required in the suggested load balancing method to determine the capacity and location of surrounding nodes. As a result, as shown in this figure, the time it takes for the suggested approach to work is when contrasted with alternative methods, it is greatly decreased. When the standard deviation of the four methods for node load is compared, the average task execution delay is checked. Fig. 9 shows that the dispersion of the nodes' loads is initially lower in the SALB algorithm than in other approaches, but that it has dramatically decreased within the suggested approach as an agent learning has increased. This demonstrates that the suggested strategy evenly distributes the duties around the network, minimizing the likelihood of overhead in the nodes.

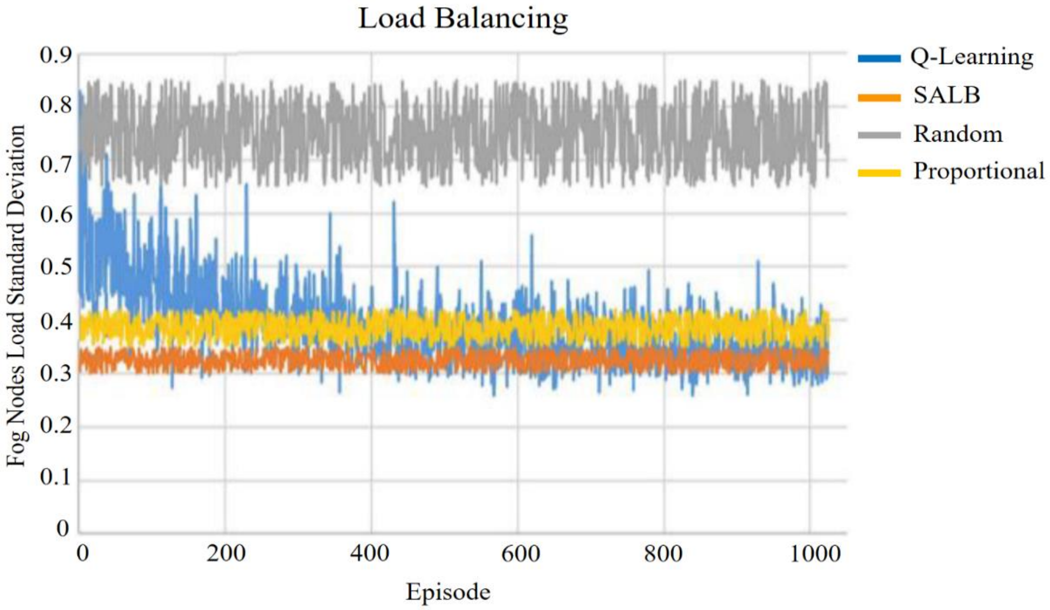

Fig. 9. Dispersion of node loads averaged out.

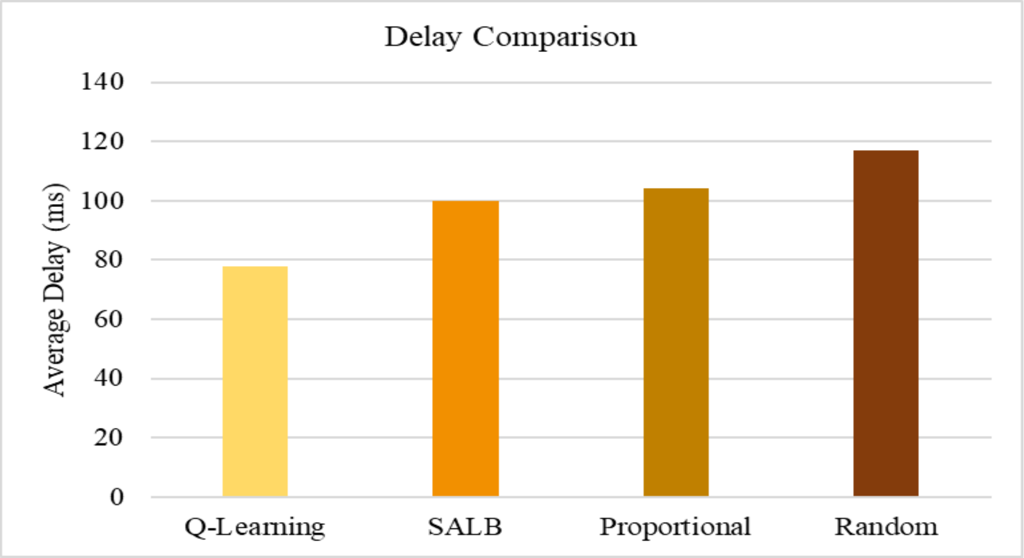

Fig. 10. Comparison of total delay for different methods.

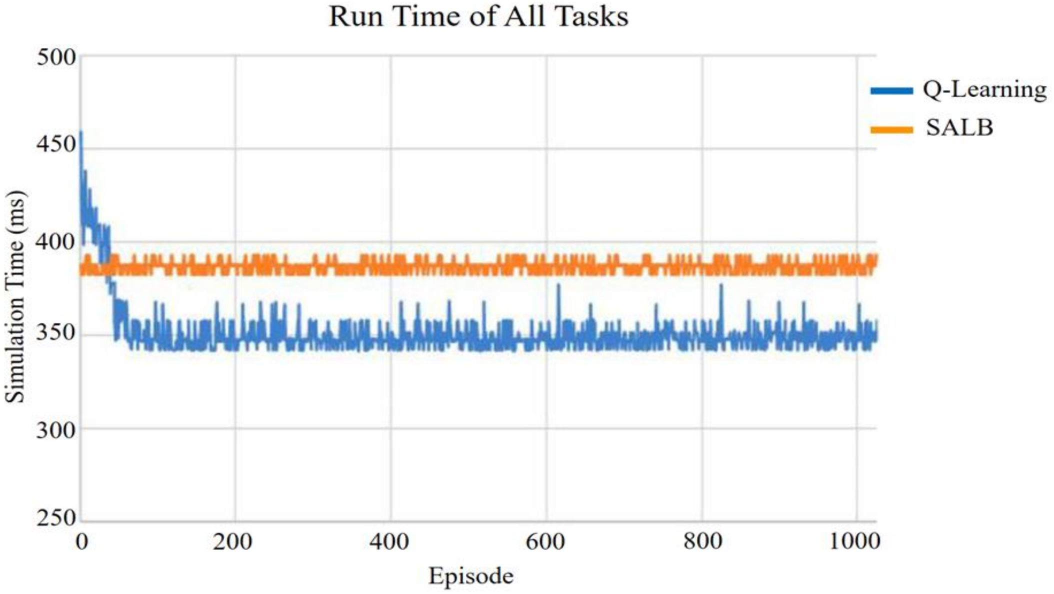

Fig. 11. Time to execute all tasks.

The overall execution time for the jobs using all four approaches is shown in Fig. 10. The average execution time of the input jobs from the first to the last algorithm iteration is used to calculate the overall delay. The examination reveals that the Q-Learning approach has the least overall delay when compared to other methods, which indicates that this method performs at a higher level of excellence.

Fig. 11 compares the execution times of both the suggested approach and the SALB method for each task that is entered into the system. The suggested solution significantly outperformed the SALB method in terms of the amount of time it took to execute all of the jobs that were input into the system during the simulation. Due to this, the suggested approach and system perform better than alternative methods that were also considered. The results show that the fog node considers the queue states, capacities, and the number of mobile devices linked to each node while deciding whether to disperse the load using the Q-Learning method. So, the unsuccessful allocation can be reduced by the proposed approach. Based on the results of the evaluation mentioned earlier, the proposed load balancing method is more stable than current load balancing approaches, and it significantly reduces both the network delay and the user response time.

VI. Conclusion

This article's goal is to outline a strategy for enhancing load balancing in fog nodes. Task distribution and load balancing are difficult problems in fog computing because of unique characteristics including topology dynamics and resource heterogeneity, and the adoption of conventional approaches to address these difficulties is inefficient. The application of machine learning algorithms, including reinforcement learning, is one of the cutting-edge methods for tackling complicated issues. In this article, the Q-Learning algorithm is used to demonstrate load balancing in a fog environment. By utilizing the experience that the learning agent acquires through interacting with the environment, this algorithm generates a long-term optimal strategy. As an agent, each fog node in the proposed technique searches the fog environment for low-load nodes suitable for allocating sub-tasks to reduce processing time and overhead with the use of the Markov decision process. The proposed solution has been tried with various numbers of mobile devices and fog nodes in the network, and it has produced successful results. According on simulation results, the suggested algorithm greatly reduces processing delay, user response time, and the likelihood of task assignment failure when compared to existing approaches. Some of the limitations of this research can include the following:

1) *Hypothetical system model:* This research assumes a system model and specific features for fog nodes, task distribution and network communication. These assumptions may not always hold true in practical deployments and potentially limit the generalizability of the findings.

2) *Limited scalability testing:* The scalability of the proposed algorithm may not have been extensively tested across a wide range of network sizes and configurations. Performance evaluation at different scales can provide valuable insight into algorithm robustness.

According to the study, the following can be considered for future research:

1) *Dynamic adaptation:* Enhancing the algorithm to dynamically adapt to changes in network conditions, such as node failures, varying workloads, or the mobility of fog nodes, to ensure robustness and scalability.

2) *Optimization techniques:* Investigate advanced optimization techniques to improve the efficiency and convergence speed of the reinforcement learning algorithm, potentially including deep reinforcement learning or other advanced methods.

3) *Security and privacy considerations:* Review the security and privacy implications of the proposed load

balancing approach, including potential vulnerabilities and mitigation strategies to protect sensitive data and ensure system integrity.

4) Integration with edge devices: extending the algorithm to combine edge devices and optimize the allocation of work in both fog nodes and edge devices, taking into account factors such as device capabilities, energy constraints, and communication protocols.

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Construction of an Art Education Teaching System Assisted by Artificial Intelligence

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***Abstract*—With the continuous progress of art education and artificial intelligence technology, traditional music teaching models are facing transformation. This article aims to construct an art education and teaching system based on artificial intelligence, especially for teaching music sound recognition. Through in-depth research, we have designed a music sound recognition system that uses Mel frequency cepstral coefficient (MFCC) for feature parameter extraction, and combines BP neural network algorithm to construct a music sound learning model. The main purpose is to improve the efficiency and accuracy of music teaching through artificial intelligence technology. The main challenge we face in this process is how to effectively extract the features of music sounds and accurately identify different tones through algorithms. By using the MFCC algorithm, we have successfully solved this problem as it can effectively describe the time-frequency characteristics of music sound. Our proposed music sound learning model is based on a BP neural network, which trains the network to learn the mapping relationship between music sound and pitch. The experiment used piano sound as an example to verify the accuracy and reliability of the system. The simulation experiments conducted in MATLAB environment show that our system can accurately recognize and extract the main frequency of music, and has higher performance compared to traditional methods.**

Keywords*—Feature extraction BP neural network; Tone recognition; smart art teaching; MEL frequency cepstral coefficient; MFCC algorithm; time frequency characteristics

I. INTRODUCTION

The Internet era's art education is progressively moving toward online and intelligent learning due to the economy's rapid growth. As a new discipline, artificial intelligence is mainly used to expand the methods and theories of human intelligence. The advent of artificial intelligence brings many opportunities for the development of science and technology but also makes art design face more challenges. The changes in market demand, the prominence of design immediacy problems, and the changes in design subjects make the existing art design face more challenges [1], [2].

Different listeners have their preferences for musical styles, and people usually experience and appreciate music from the tune, tone, and rhythm. In music dissemination, the music signal is transmitted to the human ear first; after receiving it, the human ear converts the music waveform into a bioelectric signal and then transmits it. Bioelectrical signals are transmitted to the brain through the nervous system. Finally, the brain analyzes the bioelectrical signals to further learn from the human experience of music. The brain plays a major role in the music appreciation process. In general, the role of the brain is to reduce high-dimensional musical signals to several musical dimensions that people care about, such as rhythm, melody, and harmonic intensity and intensity. These elements describe our experience and understanding of music. Therefore, learning a music data model based on music feature parameters can effectively reduce redundant data in music data and finally obtain more accurate data describing music. Tone recognition is a pattern recognition problem. There are rule-based audio classification methods, pattern matching methods, etc., but these methods still need to be improved. The rule-based audio classification method is simple to operate. Still, because of its simplicity, it is only suitable for identifying audio types with simple features, such as mute, which is difficult to satisfy for complex and multi-feature music classification applications. The pattern-matching method must establish a standard pattern for each audio type and then compare and match the input pattern with the standard pattern, which requires much computation and low classification accuracy. The hidden Markov model (HMM) method has a strong dynamic time series modeling ability, and the calculation amount is small, but the classification decision-making ability could be better. Artificial intelligence provides a good foundation for the research work of self-learning ability and automatic audio classification [3].

The modern art education system has gradually begun to be refined, including art education work evaluation, art education curriculum evaluation, and art education timeliness evaluation. In the quality evaluation of art theory courses, as early as the 1990s, some scholars in our country discussed the art education teaching system concept. Later, some domestic scholars explored and spread it, but it has yet to form a large-scale impact. The early research scholars analyzed how to improve the teaching quality of art courses from a macro level. They believed ideological teaching should integrate theory with practice, based on classroom teaching, enrich students' theoretical knowledge reserves, and strengthen display and application. Lin D. et al. [4] first proposed an intelligent system for teaching art theory courses in colleges and universities and tried to introduce artificial intelligence algorithms into art education. By exploring the application of artificial intelligence algorithms in art teaching, this paper proposes a music recognition method based on BP neural network for the problems existing in traditional music recognition methods. The cepstral coefficient method is used to extract the musical features, and the Mel cepstral coefficients are used to form the feature vector.

This article is dedicated to exploring the innovative application of artificial intelligence in the field of music sound recognition, providing intelligent and personalized solutions for art teaching. We use Mel frequency cepstral coefficient (MFCC) for feature parameter extraction and combine it with BP neural network algorithm to construct a music sound learning model to optimize the effectiveness of music teaching. Through the research in this article, we hope to bring revolutionary changes to the field of music education, achieve more efficient and precise teaching, and stimulate students' creativity and musical potential. This is not only an in-depth exploration of the application of artificial intelligence in the field of art education and teaching, but also a beneficial attempt to innovate music education and teaching methods.

II. Related Work

With the advancement of technology and the development of media art, artificial intelligence technology has penetrated into various art fields, especially in the application of complex situational teaching in folk music, which is becoming increasingly prominent. Li and Bin [5] discussed how artificial intelligence can assist in the teaching of complex folk music situations and promote the modernization of traditional folk music education from the perspective of media art. Media art, as a new field that integrates technology and art, has brought a new perspective to traditional folk music teaching. In this context, folk music teaching is no longer limited to traditional master apprentice inheritance or classroom teaching, but can realize the sharing of teaching resources and diversification of teaching methods through multimedia, Internet and other modern technical means. Complex situation teaching emphasizes teaching in actual or simulated real situations to improve students' practical abilities and ability to cope with complex situations. In the teaching of folk music, complex situational teaching is particularly important because folk music is often closely linked to specific cultural and historical backgrounds. The introduction of artificial intelligence technology has provided strong support for the teaching of complex situations in folk music. Computer assisted analysis, as a technical means, can quantitatively and qualitatively analyze artistic images. By utilizing algorithms such as image recognition, machine learning, and deep learning, CAA can deeply explore the style, techniques, themes, and other aspects of artistic works, providing insights that traditional methods find difficult to obtain. Shen [6] collected a large amount of image data from art works and analyzed them using CAA to discover the stylistic differences and evolutionary trends among different art genres and artists, thus constructing a more comprehensive and detailed theory of art history. CAA reveals the decision-making process, technological application, and style formation of artists in the creative process, which helps us understand the internal logic and laws of artistic creation and provides new theoretical support for artistic creation. Neural networks are computational models that simulate the structure of human brain neurons, with powerful feature learning and classification capabilities. In vocal speech recognition, neural networks can automatically extract sound features by learning a large amount of vocal data, achieving accurate recognition of vocal signals.

The vocal speech recognition technology based on neural networks can not only recognize basic elements such as melody and rhythm of songs, but also further analyze deeper information such as the singer's timbre, pitch accuracy, and emotions. Vocal voice evaluation is a quantitative evaluation of a singer's performance. Traditional vocal evaluation mainly relies on the subjective judgment of professional judges, while neural network-based vocal speech evaluation technology can provide more accurate and comprehensive evaluation through objective analysis of vocal signals. Neural networks can learn the evaluation criteria and preferences of professional judges, thereby achieving automatic evaluation of the singer's voice quality, skill application, emotional expression, and other aspects [7]. Mei et al. [8] explore the possibility of constructing art theory from the perspective of art images based on AI assisted analysis, and analyze its impact on art research and creation. AI assisted analysis refers to the automated and intelligent analysis of artistic images using artificial intelligence algorithms [9]. Through technologies such as deep learning and image recognition, AI can deeply explore the style, techniques, composition, and other aspects of artistic works, providing a more detailed and objective interpretation than traditional methods. This technology not only improves the accuracy and efficiency of analysis, but also provides a new perspective and method for art research. Traditional research on art history mainly relies on the knowledge and experience of experts, while AI assisted analysis can reveal the evolution laws of art styles, schools, and trends through mining and analyzing a large amount of art image data, providing a more comprehensive and objective theoretical basis for art history. AI can analyze the image data during the artist's creative process to reveal the artist's creative ideas, technical application, and style formation process. This helps us to have a deeper understanding of the internal logic and laws of artistic creation, providing new support for the theory of artistic creation [10].

Although artificial intelligence has made significant progress in the field of music recognition, it still faces many challenges and limitations. Traditional voice recognition methods often rely on manually extracted features, which are time-consuming and difficult to ensure the comprehensiveness and effectiveness of the features. In addition, musical sound has a high degree of complexity and diversity, and different instruments and performance styles can bring difficulties to sound recognition. Therefore, it is particularly important to develop a system that can adaptively, efficiently, and accurately recognize music sounds.

This article proposes a music sound learning model based on MFCC and BP neural network. Firstly, the MFCC algorithm is used to extract feature parameters of music sound, which can effectively describe the time-frequency characteristics of music sound. Then, these feature parameters are used as inputs for the BP neural network, and the mapping relationship between music sound and pitch is learned through training the network. Finally, the trained network is used to recognize new music sounds, thereby achieving the recognition and extraction of the main frequency of music.

III. Artistic Music Tone Recognition and Feature Extraction

A. Principles of Art Music Tone Recognition

There are two main recording formats for artistic musical tone information: WAVE format and Musical Instrument Digital Interface (MIDI) format. MIDI is a standard for transmitting music signals between electronic musical instruments. It includes hardware interface standards and asynchronous serial transmission protocols for electronic music signals between different hardware. The transfer rate is 31.25k (±1%) baud. Since the music file in MIDI format records the whole process of the score and performance, many basic features of music can be directly extracted. Therefore, the identification of music features mostly adopts the music files in MIDI format, and this paper mainly aims at identifying the music files in MIDI format.

From the physical level analysis, music consists of the fundamental frequency, frequency multiplication, and signal amplitude. These three factors correspond to three important concepts in musicology. The physical quantity determined by the fundamental frequency of the musical tone signal is called pitch. The fundamental frequency and the multiplied frequency signal jointly constitute the requirements for the timbre. Finally, the amplitude of the signal is the sound intensity in musicology. From the level of emotional characteristics, pitch, length, timbre, fundamental tone, tone name, and rhythm are six vectors that reflect the characteristics of music.

1) Pitch: The higher the pitch of the signal, the higher the dominant frequency, and vice versa. However, the corresponding relationship between pitch and dominant frequency is not a simple linear relationship but an approximate logarithmic relationship.

Changes in pitch can be expressed in tunes. For singers, the pitch mainly reflects the changes in the singer's voice. For music sung by a soprano singer, the frequency of the music signal is higher. For bass singers, the signal frequency is very low during music analysis. In the process of picking up musical tones, it is common to detect the length of time between peaks and the amplitude of the peaks. The smaller the amplitude, the smaller the pitch. The amplitude cannot represent the pitch, and the frequency must be considered comprehensively. In this way, the displayed tones are the high and low frequencies.

Define *f* as a function that evaluates the pitch attribute of a MIDI file. The musical emotion of a MIDI song file is mainly reflected in the master track. Let the number of audio tracks be *m*. In the process of identifying the emotion of the music, the relevant extraction of the pitch characteristics of each audio track, such as the average value of the pitch characteristics of each audio track, is carried out, and determine the pitch feature vector x_f of the piece according to the corresponding properties of the main audio track. Therefore, suppose that the type of music emotion to be detected is *n*, $n \geq 1$, and the eigenvalue of the emotion type under the action of the current pitch value is $pi(xf)$, $i\in$ [1, 2, ..., n], then each emotion the part of the type related to the pitch attribute index of the song, as shown in Formula (1).

$$f(x_f) = Max(p_i) \tag{1}$$

2) Length: To measure the pitch characteristics of a musical piece, a function g is defined as an evaluation standard. Generally speaking, the longer the pitch, the more sad and melancholy elements it expresses in the emotional components. In the pitch identification of MIDI files, the pitch attribute is mainly determined according to the length of its duration. Define the threshold value of the pitch length switch as x_{switch} and the interval of note switch as x_g, then the value of the pitch length evaluation function g is as follows:

$$g(x_g) = \begin{cases} long, x_g < x_{switch} \\ short, x_g > x_{switch} \end{cases} \tag{2}$$

3) Tone: In the MIDI standard, 128 timbres are defined. 128 timbres are divided into k categories, and the function h for extracting the timbre features of the current music is as follows:

$$h_{x_i} = \begin{cases} 1, x_i \in C_1 \\ 2, x_i \in C_2 \\ \ldots \\ M, x_i \in C_M \end{cases} \tag{3}$$

4) Fundamental and overtones: The fundamental tone is the main frequency, which is the trigger frequency when the piano strings vibrate over the full length; the overtone, also known as the harmonic frequency, is the vibration frequency at which the strings are triggered in the non-full field. From the physical characteristics of the above analysis, it can be known that the fundamental frequency is the lowest frequency of vibration triggered by the strings. The values of overtones are integer multiples of the fundamental. In the normal operation of the piano, the fundamental tone determines the pitch of the tone, and the fundamental tone and the overtone together determine the timbre of the tone of the signal.

5) Sound name: The so-called sound name is the name attribute of a certain musical sound. Often referred to in music, octaves correspond to octaves in signal processing. That is, the pitch of two single notes differs by one octave, and the main frequency value differs by one time. Divide one octave of the signal into 12 semi-treble pitches: C, #C, D, #D, E, F, #F, G, #G, A, #A, B. There is the tone name of the tone signal or the fundamental tone level. The name of the piano is based on the twelve-tone equal temperament system.

6) Rhythm: Different music has different emotional matting speeds. The basic understanding is that some music is fast and others are slow. For example, Disco music gives us a sense of speed. In contrast, blues music is slower and emotionally sad, and this music can display the number of syllables output per second or minute by digitizing the rhythm. After noise reduction, the computer detects the number of audio signal peaks per minute. The number of peaks per minute can accurately express the rhythm of speech. Then, by extracting the signal envelope and marking the peaks of the envelope contour, the envelope peak value per second of the whole music is calculated and recorded as the peak frequency, which is used to measure the rhythm intensity of the music. Peak frequency means that the music has a strong rhythm. Generally speaking, this music is mainly disco.

B. *Extraction of Musical Tone Features*

As shown in Fig. 1, the identification of musical functions can also be divided into three levels: basic musical functions, complex characteristics, and general musical characteristics.

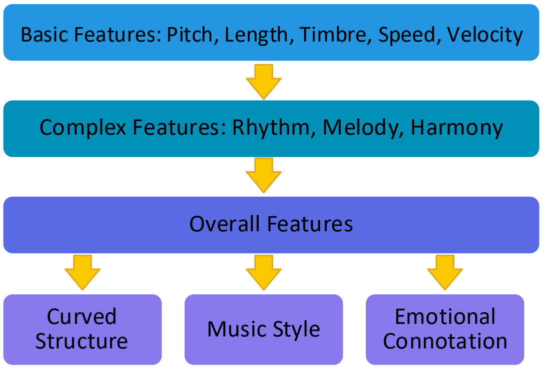
Basic Features: Pitch, Length, Timbre, Speed, Velocity
Complex Features: Rhythm, Melody, Harmony
Overall Features
Curved Structure
Music Style
Emotional Connotation

Fig. 1. The characteristic structure of music.

After preprocessing the musical tone signal, the next thing to do is to digitize the musical tone signal and extract its characteristic parameters, that is, replace the entire musical tone signal with a set of characteristic parameters the computer can process. This link is crucial and directly related to the performance of the recognition model in the next link. Feature extraction, or front-end processing, is crucial in recognizing musical tones. Measuring the distance between feature parameters to determine the intrinsic features of musical sounds is the fundamental step in its extraction process. In musical tone recognition, the characteristic parameters generally used are parameters that can reflect the short-term spectral envelope. The mainstream algorithms include Linear Prediction Cepstrum Coefficient (LPCC) and Mel Frequency Cepstral Coefficients (MFCC) f.

When configuring the implemented tone recognition algorithm, a series of parameters need to be set for each algorithm. These parameters will affect the performance and accuracy of the algorithm. The following are several aspects that typically need to be considered when configuring parameters for linear prediction cepstral coefficients (LPCC) and Mel frequency cepstral coefficients (MFCC):

1) Filter order: This refers to the order of the filter or model used for linear predictive analysis. It determines the complexity of the dynamic characteristics of the sound signal that the model can capture. A higher filter order can capture finer structures, but it may also lead to overfitting and increased computational complexity.

2) Window function and window length: The window function and window length used to analyze sound signals determine the time resolution and frequency resolution of the analysis. The commonly used window functions include the Hamming window and the Hanning window. The window length is usually selected based on signal characteristics and the required time-frequency resolution.

3) Pre emphasis: In order to eliminate possible DC bias during the sound production process, pre emphasis is usually performed before signal analysis. Pre emphasis is usually achieved by applying a high pass filter.

4) Iteration count: When solving the LPC coefficient, multiple iterations may be required to converge to a stable solution. The number of iterations should be sufficient to ensure convergence, but excessive iterations may increase computation time.

The linear prediction cepstral parameters (LPCC) map the linear prediction parameters (LPC) in the cepstral domain. Cepstral technology is a well-known homomorphic signal processing method, and its calculation steps generally need to go through the following three steps: fast Fourier transform, logarithmic operation, and phase correction. The LPCC feature extraction algorithm assumes that the musical sound signal is autoregressive and uses the LPC parameters to obtain the cepstral coefficients. The LPCC parameters are insufficient for the anti-noise performance of the system. In the normal range of use, noise signals will inevitably be, which may lead to large errors in the final recognition results. Therefore, MFCC parameters with an anti-noise performance ratio are generally used as a feature extraction method for musical sound signals in practical applications.

5) MFCC: Based on Fourier and cepstral analysis, the spectrum in the time domain can be transformed through the nonlinear spectrum and finally converted to the cepstral spectrum for research. One of its major features is its good identification effect and anti-noise ability, but its calculation amount is complicated compared with LPCC. MFCC reflects the pitch auditory characteristics of the human ear, and it is not computationally intensive and is widely used in speech processing. The research results show that MFCC can be used as an audio classification feature and can improve the accuracy of audio classification. Among them, the relationship between the Mel scale and the specific time domain frequency is shown in Fig. 2.

The calculation process of the MFCC feature is as follows:

The MFCC parameters rely on the Mel frequency filter bank of equal bandwidth set by it, perform D transformation on each frame of signal to calculate the amplitude spectrum, and then transform the amplitude spectrum into the Mel domain with the Mel scale, and filter by the Mel filter bank of equal bandwidth.

$$e[j] = log\left(\sum_{k=0}^{N-1} w_j[k] \times |s[k]|\right), j = 1,2,\ldots.,p \qquad (4)$$

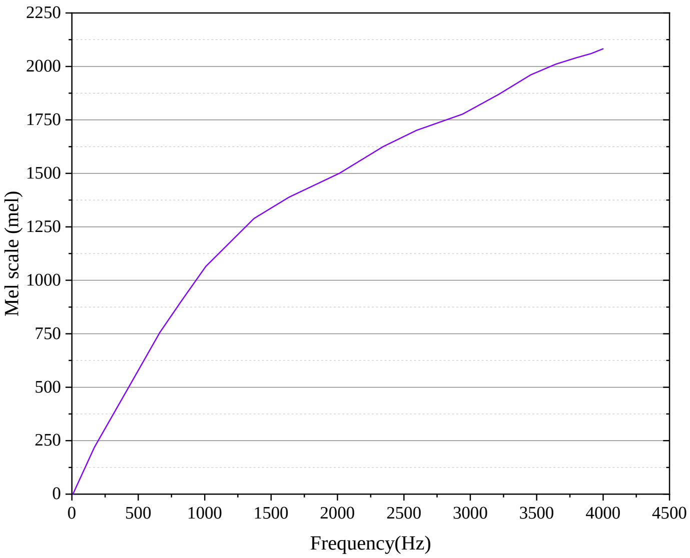

Fig. 2. Relationship between mel scale and frequency in the time domain.

Where: $e[j]$ represents the logarithmic energy output of the jth filter; $w_j[k]$ represents the weight corresponding to the kth point of the jth triangular filter; $|s[k]|$ represents the transformation to Mel scale Discrete Fourier Transform (DFT) spectrum amplitude on; P is the number of filters, generally 24. Taking the discrete cosine transform of the logarithmic energy of the filter, the following cepstral domain MFCC coefficients can be obtained:

$$x_i = \sqrt{\frac{2}{p}}\sum_{j=1}^{p}\left(e[j] \times cos\left(\frac{i\pi}{p}(j-0.5)\right)\right), i = 1,2,\ldots,L \quad (5)$$

Among them, L is the dimension of the MFCC. Generally, $L \leq P$, this paper takes 12 dimensions.

The MFCC dynamic characteristic parameters of the music signal can mainly be described by the different spectrums of these static characteristics, combining the first-order and second-order differences as the dynamic feature. These dynamic and static information complement each other, which can greatly improve the recognition performance of the system [11].

C. Research on Tone Recognition Model

After introducing the first two important links of the music sound recognition system, the related algorithms of preprocessing and feature parameter extraction, the system needs to match the model, which is the most important link in the music sound recognition process, matching the optimization degree of model training. The recognition rate of matching using this model is closely connected to it. Consequently, the training of the model is crucial for accurately recognizing musical tones, and users must supply numerous original databases. Therefore, it is necessary to establish a musical tone database before starting the musical tone recognition research. A collection of 88 piano syllables recorded in various settings is available in the database. The individual file should be distinct from others and accurately represent the original musical sound data in a well-balanced way. The essence of model training is to extract the inherent connections and laws of the data using a large amount of data under certain training standards. The unknown musical tone signal is used as input to act on the model, and it is matched and compared to see which template library data is more closely related to obtaining the recognition result. The training process related to the recognition rate of the entire system must meet the training of large data volume and the high efficiency of learning speed.

Artificial neural network (ANN) is a frontier research field for simulating human brain structure and thinking process. ANN can continuously adjust their parameters in training process weights and topology structure to adapt to the environment and the demand of the system performance optimization; it has the characteristics of fast speed and high recognition rate in pattern recognition and has been the research direction and hotspot of music recognition system at home and abroad.

In general, the neural network-based music sound recognition system has great potential for development. Still, the research on the application method for large-scale problems has just started, especially for the actual music sound recognition system. Neural networks generally have the disadvantage of too long training and recognition time.

IV. Realization of Intelligent Art Education System

A. Analysis of BP Neural Network Algorithm

The core algorithm model of the intelligent art teaching system adopts the back-propagation network. The learning algorithm of error backpropagation to train and adjust the weights of the nonlinear differentiable functions of the multi-layer network. It belongs to the multi-layer forward feedback neural network, and the activation function of its neurons belongs to the sigmoid function, which can complete any nonlinear mapping from the input layer to the output layer.

Theoretically, any nonlinear signal can be approximated if the system has one or more S-functions. Therefore, the recognition accuracy can be enhanced through increasing the number of network layers. Still, with the increase of the network layers, the network learning time and calculation amount will also increase significantly, leading to a decrease in the relative performance of the system. Therefore, some balance must be struck between recognition progress and system speed. Generally speaking, the three-layer structure of the BP network, that is, the single-hidden layer network, can achieve a balance between the two by increasing or decreasing the number of neurons in the hidden layer. In the specific design, different numbers of neurons in the hidden layer can be used for experimental comparison to obtain the optimal number of neurons in the hidden layer. Fig. 3 shows the basic structure of the BP neural network, which includes three-layer architecture of input layer, hidden layer, and output layer.

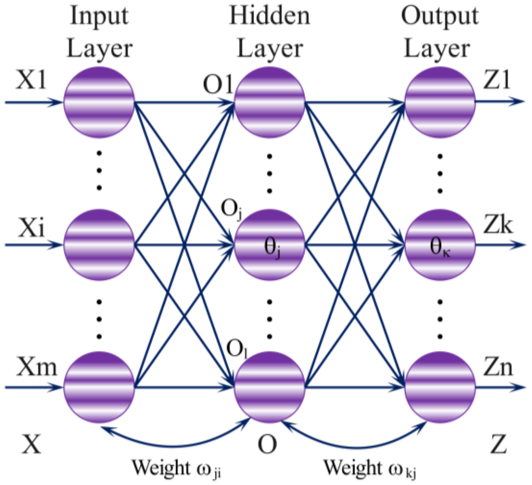

Fig. 3. BP neural network structure.

The first layer is the input layer. For the intelligent art teaching system, the quantities input to the BP neural network can be summarized as the characteristic parameters of the music signal. Set the input sample pair as (X, Y), where the input layer variable X is m, corresponding to n expected values Y.

The second layer is the hidden layer. The number of neurons in the hidden layer O is l. According to the function transfer formula of the hidden layer, the output expression of the jth hidden layer neuron O_j is:

$$O_j = f(\sum_{i=1}^{m} \omega_{ji} x_i - \theta_j), \quad j = 1,2,\cdots,l \tag{6}$$

Among them, ω_{ji} is the weight between the jth hidden layer neuron and the ith input layer neuron, θ_j is the threshold of the jth hidden layer neuron, and f is the hidden layer transfer function [11].

The third layer is the output layer, which outputs the evaluation index of the note signal. The output expression of the kth neuron z_k of the output layer is:

$$z_k = g(\sum_{j=1}^{l} \omega_{kj} O_j - \theta_k), \quad k = 1,2,\cdots,n \tag{7}$$

Among them, ω_{kj} is the weight between the kth output layer neuron and the jth hidden layer neuron, θ_k is the threshold of the kth output layer neuron, and g is the output layer transfer function [12], [13].

It is clear that the error E between the output value z_k and the expected value y_k is:

$$E = \frac{1}{2}\sum_{k=1}^{n}(y_k - z_k)^2$$
$$= \frac{1}{2}\sum_{k=1}^{n}\{y_k - g[\sum_{j=1}^{l}\omega_{kj} f(\sum_{i=1}^{m}\omega_{ji}x_i - \theta_j) - \theta_k]\}^2 \tag{8}$$

In the BP neural network, iteration aims to correct the weights and thresholds so that the error function E can decrease at the fastest speed. Taking the negative gradient direction makes the error function decrease the fastest, which is also very consistent with the teaching model of the influencing factors of interactive art learning [14], [15].

It can be seen that to ensure that the predicted value is as close to the expected value as possible, the correction formulas of the weights and thresholds in the iterative process must satisfy the following formulas

$$\begin{cases} \omega_{ji}(t+1) = \omega_{ji}(t) + \Delta\omega_{ji} = \omega_{ji}(t) - \lambda_1 \frac{\partial E}{\partial \omega_{ji}} \\ \omega_{kj}(t+1) = \omega_{kj}(t) + \Delta\omega_{kj} = \omega_{kj}(t) - \lambda_2 \frac{\partial E}{\partial \omega_{kj}} \\ \theta_j(t+1) = \theta_j(t) + \Delta\theta_j = \theta_j(t) - \lambda_1 \frac{\partial E}{\partial \theta_j} \\ \theta_k(t+1) = \theta_k(t) + \Delta\theta_k = \theta_k(t) - \lambda_2 \frac{\partial E}{\partial \theta_k} \end{cases} \tag{9}$$

where, t is the number of iterations, and λ_1 and λ_2 are the hidden and output layers' learning rates, respectively [16], [17].

B. BP Neural Network Learning Steps

Learning the BP neural network involves the following special steps s follows:

The first step is to initialize the connection weights and thresholds of the entire network, assign the connection weights ω_{ji}, ω_{kj} and the thresholds θ_j, θ_k to any number within (-1, 1) respectively, set the error function E, and determine the calculation accuracy and the maximum learning times M of the BP neural network [18]–[20].

The second step randomly selects the ith input sample and the corresponding expected output: X_i= [x_1, x_2, ... , x_i], Y_i=[y_1, y_2, ... ,y_i].

The third step is to calculate the input value and output value of each neuron in the hidden layer.

The fourth step is to calculate the partial derivative of the error function for each neuron in the output layer according to the error between the expected output value of the BP neural network and the theoretical value, as shown in Formula (10).

$$\frac{\partial E}{\partial z_k} \quad (k = 1,2,\cdots,n) \tag{10}$$

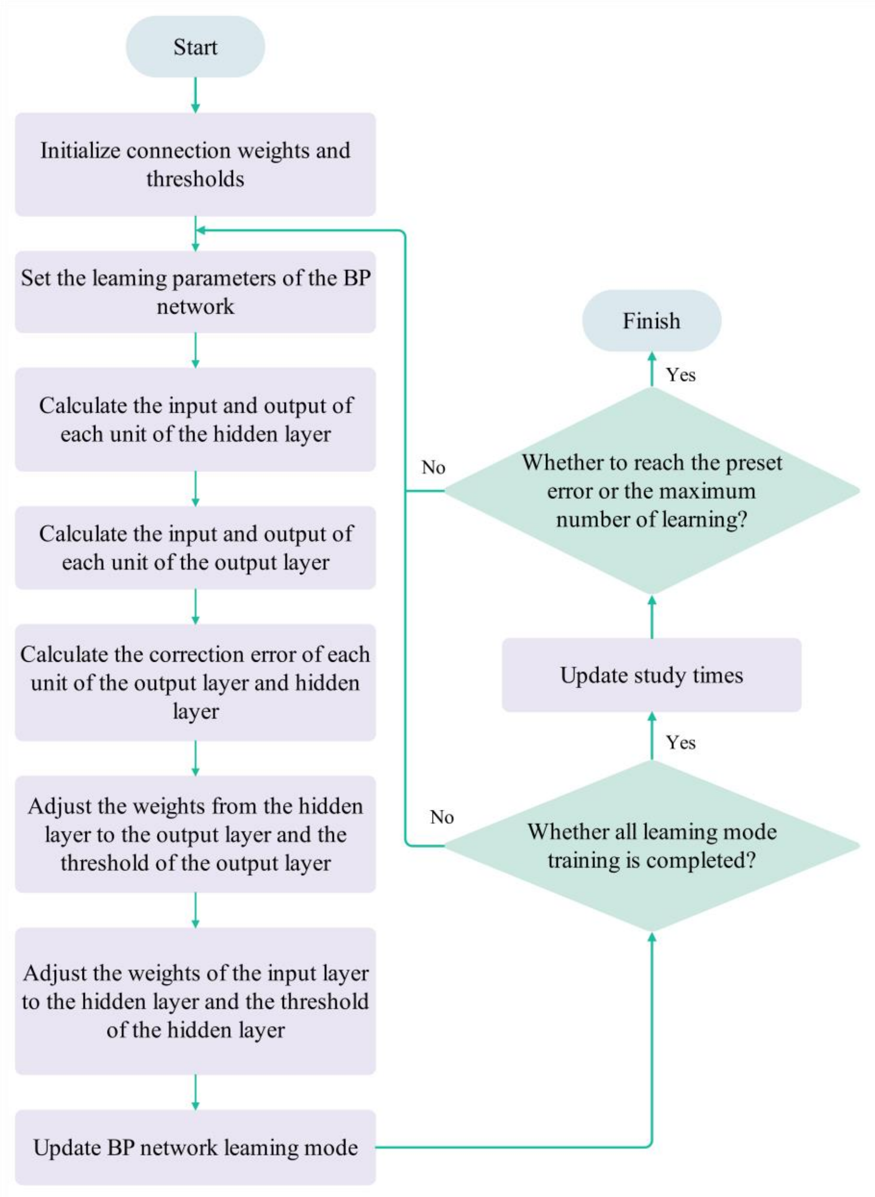
Start
Initialize connection weights and thresholds
Set the leaming parameters of the BP network
Calculate the input and output of each unit of the hidden layer
Calculate the input and output of each unit of the output layer
Calculate the correction error of each unit of the output layer and hidden layer
Adjust the weights from the hidden layer to the output layer and the threshold of the output layer
Adjust the weights of the input layer to the hidden layer and the threshold of the hidden layer
Update BP network leaming mode
Whether all leaming mode training is completed?
No
Yes
Update study times
Whether to reach the preset error or the maximum number of learning?
No
Yes
Finish

Fig. 4. BP neural network learning steps.

Step five involves calculating the derivative of the error function for each neuron in the hidden layer concerning the connection weight between the hidden and output layers, the derivative of the output layer, and the output value of the hidden layer, following the Formula (11).

$$\frac{\partial E}{\partial o_j} \quad (j = 1,2,\cdots,l) \tag{11}$$

Step six involves updating the connection weights based on the partial derivatives of each neuron in the output layer and the output of each neuron in the hidden layer [21], [22]

In the seventh step, the connection weights are updated according to the partial derivatives of each neuron in the hidden layer and the input of each neuron in the input layer.

The eighth step is calculating the global error, as shown in Formula (8).

In the ninth step, randomly select a new input sample as the BP neural network input and return to the third step until all input samples are trained.

The tenth step is to randomly re-select an input sample from the *m* input samples and return to the third step until the global error function *E* of the entire network is less than the preset precision [23]–[26].

The flowchart of the BP algorithm is shown in Fig. 4.

C. *The Software Basis of Art Teaching System*

The BP network structure of the music intelligent system has been stated as before. The intelligent system operates in a combination of software and hardware. A database server is arranged in the server environment, and the system is set to 8G memory, 500G solid-state hard disk, dual CPU processors system, and Gigabit Ethernet. The software adopts SQL Server

2000 as the database management system. SQL Server contains many tools for databases that can store, retrieve, and manage databases using the SQL language and GUI applications [27].

Ideal for mobile, wireless, and embedded applications, SQL Server CE provides important relational database functionality in a compact form factor, along with flexible data access and the familiar SQL Server experience. Extending enterprise applications to .NET Compact Framework greatly enhances the development of the user's mobile space.

SQL Server 2000 provides the same performance as many advanced database managers.

1) Rich programming interfaces and development tools: Query Analyzer is provided as a development tool for writing Transact-SQL script programs. Query Analyzer provides users a graphical working environment for writing and debugging Transact-SOL programs. Supports most commonly used database application programming interfaces, such as ADO, OLE DB, ODBC, etc. These tools allow programmers to directly control the interaction between the hemp program and the database and include APIs such as ADO that support rapid program development. These tools can develop a database application program with strong functions quickly.

2) Dynamic automatic management and configuration: SQL Server 2000 can be configured autonomously and dynamically during operation. For example, when the task of the database service increases, it will dynamically and autonomously apply for more system resources; when the work is reduced, the system resources will be released; when data is inserted or deleted in the database, the size of the database can be automatically adjusted to Adapt to new situations [28], [29].

3) Dynamic realization of database concurrency control: In SQL Server 2000, row-level blockade can be implemented on data. When dealing with the concurrency control problem of the database, the strength of data blocking will be dynamically adjusted according to different situations to achieve the best state of data blocking and sharing. For example, when a query needs to access a limited amount of data in a table, a row-level lock will be added to the data; when a query needs to access the vast majority of data in a table, a page-level lock will be added to the data, and take steps to make this query complete as quickly as possible. All the concurrency control performed by SQL Server 2000 is performed automatically in the background, and users do not need to interfere and participate [30].

V. Verification of Intelligent Art Teaching System

A. System Parameter Settings

In the BP neural network, the input layer uses 12 neurons, which are used to correspond to the 12-dimensional characteristic parameters of the musical sound signal; the output layer uses one neuron, which corresponds to the main frequency of the musical sound; the number of neurons in the hidden layer is 20.

Taking the piano music as an example to verify the system, considering that the piano keys only contain 88 keys, the data is relatively small, so choose a dedicated microphone and sound acquisition card to collect the 88 keys of the piano three times and use MIDI The format saves 264 musical sound data, forming the BP neural network input unit, normalized processing of the input data, and using the MATLAB toolbox to directly read the musical tone signal, main frequency value assigned to every note is known as the training output unit.

By setting the relevant decomposition filter bank in MATLAB, the musical sound signal is decomposed by Daubechies 4th-order wavelet, and the low-pass decomposition coefficients are retained. After that, the wavelet is reconstructed by setting the low-pass reconstruction filter bank, and the removal of high-frequency components is obtained. The perfect signal is Fourier transformed to obtain its spectrogram, as shown in Fig. 5.

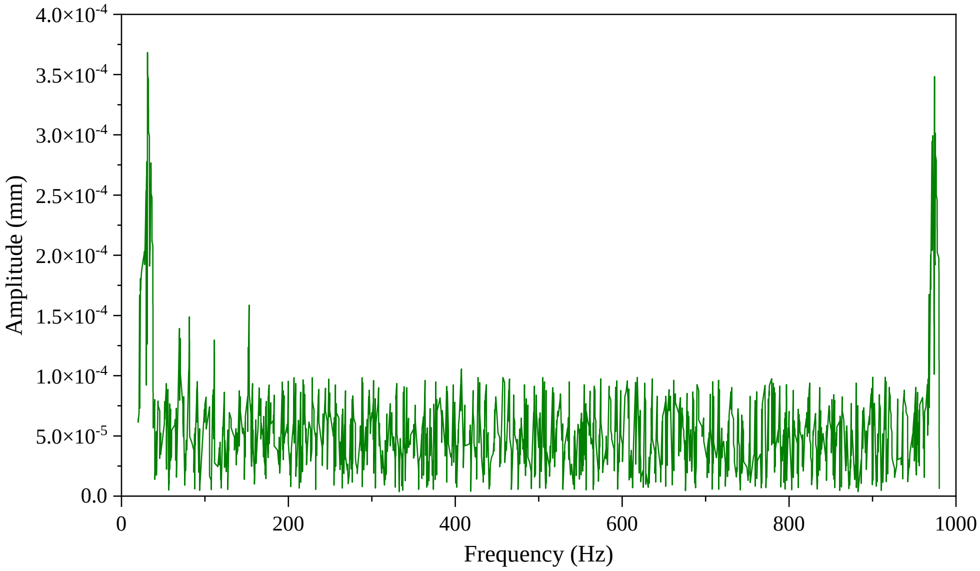

Fig. 5. Spectrogram of fourier transform.

B. Feature Parameter Extraction

After analyzing the characteristic parameters of the MFCC algorithm, a 12-order extraction algorithm has been chosen for the accuracy of musical tone recognition and to balance the amount of calculation. The length of the audio signal FFT transformation is 256, with a sampling frequency of 20500Hz and each frame having a length of 256 points. Then, the music file passed the Fourier transformation is read, and the Melbankm function normalizes the Mel filter bank coefficients. After that, the DCT parameters are solved, the pre-emphasis filter is filtered, and the music signal is re-framed. Ultimately, the musical sound signal's MFCC parameters are extracted, and the five frames of characteristic parameters are taken, as shown in Fig. 6.

C. Result Analysis

Select the characteristic parameters of 234 keys as the input of the training data and the corresponding main frequency value as the expected output result of the training, set the input neuron to 12, the output neuron to 1, the number of hidden layer neurons to 20, the maximum number of iterations is 2000, and the expected error is 10e-9. The BP neural network is trained in MATLAB, and the remaining 30 key characteristic parameters are selected as verification data. The error performance curve of the system is shown in Fig. 7. It is evident that after 1943 training times, the error reaches 10e-9.

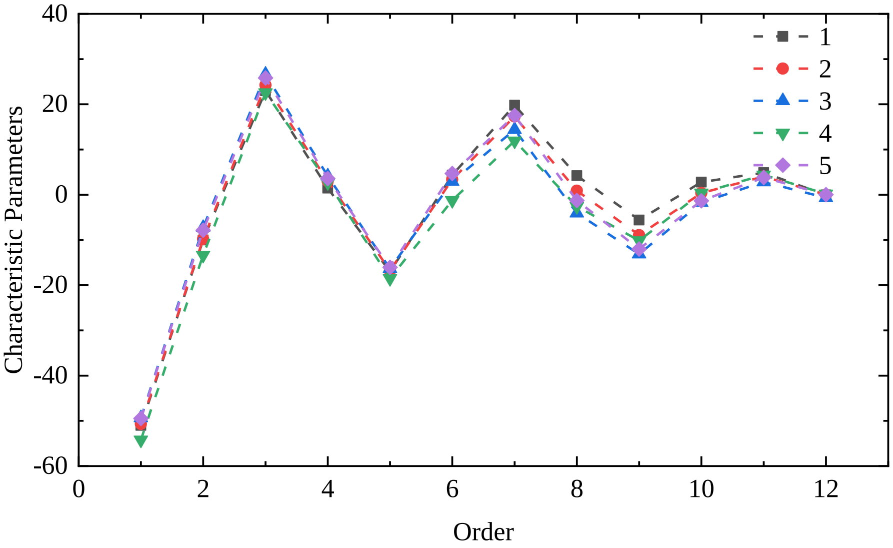

Fig. 6. Characteristic MFCC parameters.

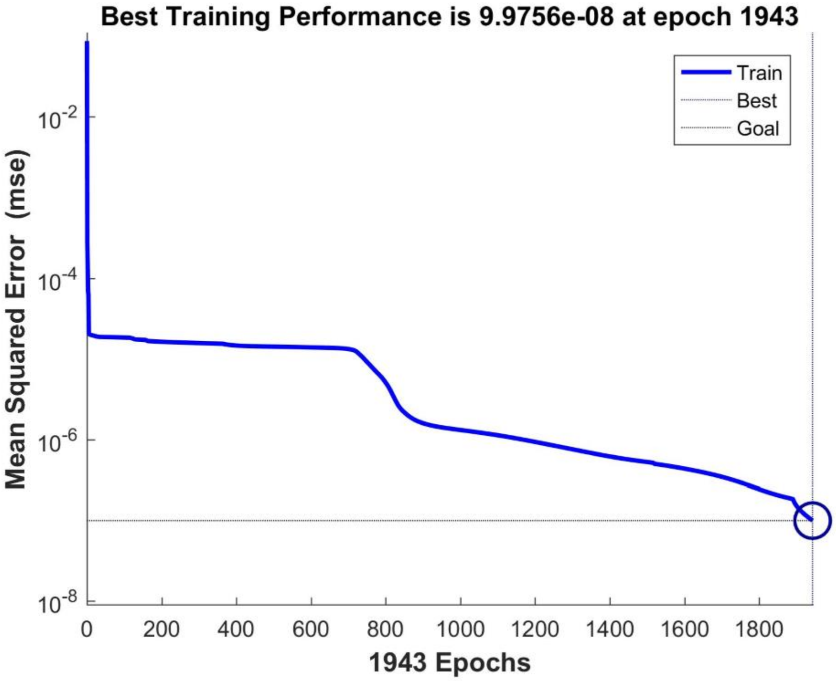

Fig. 7. BP network training performance.

The output result of the music sound teaching system using MFCC parameters as characteristic parameters for BP network matching is shown in Fig 8. It is observed that the expected value of the main frequency signal and the predicted value are consistent, with a relatively high recognition rate. It verifies the correct feasibility of the route proposed in the current paper using the BP neural network algorithm for musical tone recognition. However, from the identification results of musical tones in Table I and the relative error values in Fig. 9, it is clear that due to the compromise in wavelet filtering, identification errors in different situations will occur in low-frequency signals outside the selected area, while the relative error values of individual samples larger, which requires further investigation in subsequent studies.

TABLE I. TONE RECOGNITION RESULTS

Number	Expected value	Expected pitch names	Predictive value	Predictive pitch names
1	2637	E7	2586.67	E7
2	30.87	B0	29.2	A#0
3	220	A3	218.66	A3
4	523.2	C5	521.78	C5
5	49	G1	50.65	G#1
6	740	F#5	738.12	F#5
7	493.9	B4	497.43	B4
8	587.3	D5	585.98	D5
9	1175	D6	1172.56	D6
10	87.31	F2	85.55	F2
11	110	A2	108.82	A2
12	207.6	G#3	207.3	G#3
13	277.2	C#4	276.78	C#4
14	880	A5	878.28	A5
15	698.5	F5	697.99	F5
16	1661	G#6	1559.78	G#6
17	1245	D#6	1243.91	D#6
18	1760	A6	1756.5	A6
19	32.7	C1	31.34	B0
20	233.1	A#3	231.76	A#3
21	2794	F7	2789.66	F7
22	1661	G#6	1657.87	G#6
23	1109	C#6	1105.96	C#6
24	622.2	D#5	621.4	D#5
25	98	G2	97.6	G2
26	123.5	B2	124.1	B2
27	196	G3	194.85	G3
28	830.6	G#5	831.5	G#5
29	58.27	A#1	57.91	A#1
30	155.6	D#3	154.22	D#3

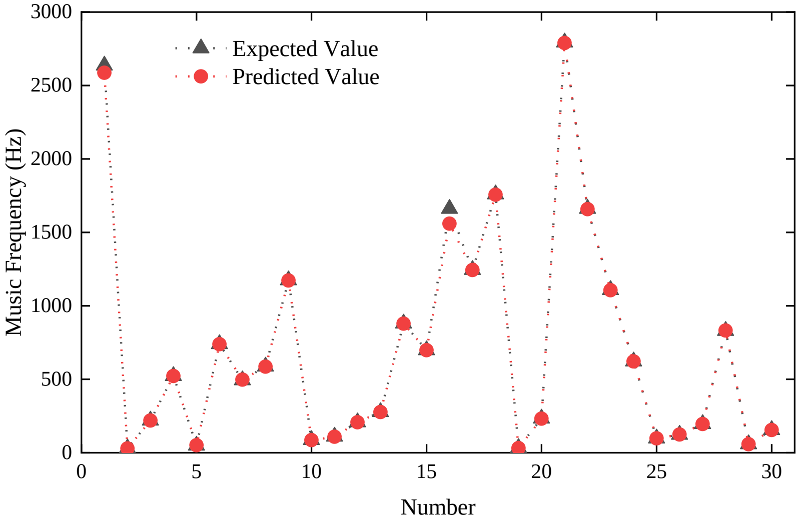

Fig. 8. Expected value and predicted value of main frequency.

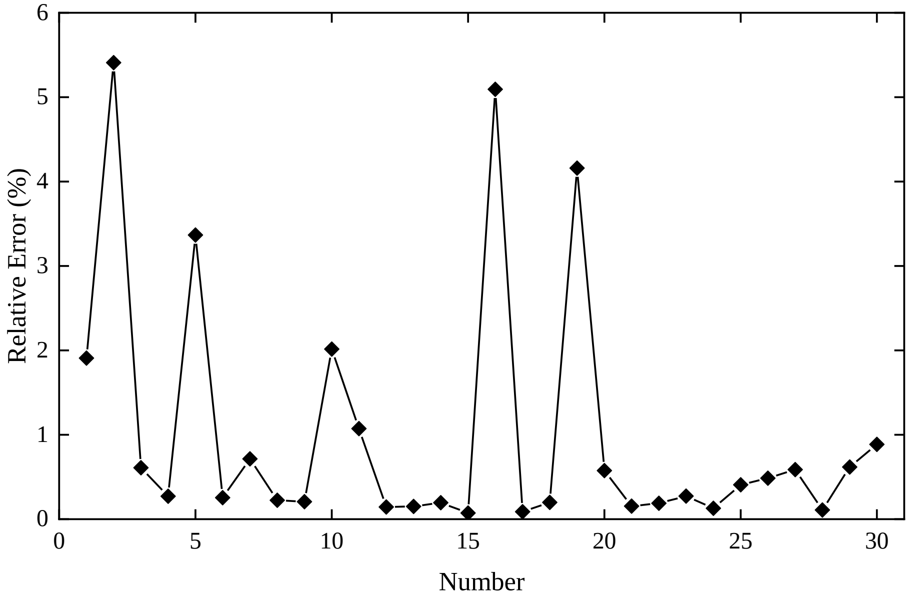

Fig. 9. Relative error between expected value and predicted value.

VI. Conclusion

The intelligent music teaching system can provide better learning concepts for art learners. Feature parameter extraction is done via MFCC, which is based on the BP neural network intelligent algorithm, and SQL Server is used as the music database management system to build a network matching of music signals to realize better the effect of the interactive teaching music intelligent system. This paper uses the piano sound signal to verify the system, and the BP learning algorithm is built in MATLAB. The verification results show that the predicted value of the network has achieved a high recognition effect, but there are certain errors in individual areas. The next research phase will involve using larger-scale model samples to realize artificial intelligence, resulting in improved accuracy across a wider range of applications. This will ensure greater stability in terms of usability and the ability to integrate various artificial intelligence algorithms to enhance the training algorithm of neural networks and create a more universal music intelligence system.

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Competing of interests

The authors declare no competing of interests.

Authorship Contribution Statement

Xianyu Wang: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Xiaoguang Sun: Methodology, Software, Validation.

Data Availability

On Request

Declarations

Not applicable

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Design of Big Data Task Scheduling Optimization Algorithm Based on Improved Deep Q-Network

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***Abstract*—Big data analysis can provide valuable insights not easily obtained from traditional data scales. However, addressing scheduling issues in big data can be challenging due to the vast amount and diverse nature of the data. To overcome this, a scheduling model based on Markov decision process is proposed. The deep Q-network algorithm is used for directed acyclic graph task scheduling. To improve this model further, the gradient strategy algorithm is introduced. From the results, when the dataset size was about 500, the hybrid algorithm achieved a recall rate of 0.96, outperforming the gradient strategy algorithm (0.83), deep Q-network algorithm (0.79), and estimated earliest completion time algorithm (0.63). Although the estimated earliest completion time algorithm had longer training times under different dataset sizes, the hybrid algorithm's training time was slightly longer than the gradient strategy algorithm and slightly shorter than the deep Q-network algorithm. Overall, the proposed algorithm exhibits superior performance and significant value in solving engineering problems.**

Keywords—Big data; Task scheduling; Policy gradient; Deep Q-network

I. Introduction

Big data refers to a data collection generated due to its large volume, diverse types, and inability to be processed by traditional processing methods. These data typically have high speed and high diversity [1]. Compared with traditional data, big data has a larger data scale, more data types, and lower value density [2]. The data volume of big data is basically calculated at the PB level. Therefore, analyzing big data requires extremely high computational power. However, at current, the processing power of a single processor has reached its limit. Relying solely on increasing processor frequency cannot meet the current demand for big data analysis. Influenced by the development of cloud computing technology, more enterprises and research institutions are inclined to use big data analysis platforms to complete data analysis work. Traditional task scheduling algorithms are usually based on static rules, which may be inflexible and unable to adapt to real-time changing environments. In the big data environment, the nature of tasks and the availability of resources may dynamically change, which makes traditional algorithms unable to effectively cope. Some traditional algorithms may become complex when processing large-scale data, leading to an increase in computational complexity. Meanwhile, it is easy to fall into local optima, which can affect the performance of task scheduling. Therefore, a scheduling model based on Markov decision process is proposed. This model applies the Deep Q-network (DQN) algorithm to task scheduling in Directed Acyclic Graph (DAG). Then, to address the shortcomings of the DQN algorithm, a Policy Gradient (PG) algorithm is introduced to improved it. The research content has four parts. The first part briefly introduces the research topic of scheduling optimization models. The second part is to analyze the main methods used in this study. The third part analyzes the results. The fourth part is a summary for the study and prospects for future research.

II. Related Works

The scheduling model is a model established for scheduling problems. Ammari A C et al. proposed a scheduling strategy based on an improved firefly algorithm for delay constrained applications in distributed green data centers. Multiple heterogeneous applications were efficiently scheduled with less cost and energy. The proposed scheduling strategy model based on the improved firefly algorithm could meet the scheduling problem of distributed green data centers [3]. With the development of cloud and mobile applications, the integration demand for applications and services in business processes is also increasing. Many integrated platforms used heuristic algorithms to schedule tasks executed by computing resources. Therefore, Freire D L et al. proposed a queue priority algorithm. This algorithm was based on particle swarm optimization, which could handle massive amounts of data in integrated task scheduling. The algorithm could execute the integration process and schedule the data under high data volume [4]. Zhou J et al. found that crowd perception could solve the massive data collection faced by most data-driven applications. Therefore, a workflow framework was first proposed, which captured the unique execution logic of perception tasks. Then, a phased approach was proposed to decouple the original scheduling problem. From the experimental results, the proposed model had good performance in solving scheduling problems [5].

Mishra A et al. found that task scheduling was crucial for improving the performance of large-scale collaborative and distributed electronic science applications. Therefore, a meta-heuristic crow search algorithm was proposed to address the scheduling problem of multiple tasks across heterogeneous virtual machines. This method could demonstrate better model performance compared with traditional models [6]. The computing demand in various application fields is increasing day by day. To meet this requirement, on-site programmable gate arrays have been widely used. Therefore, Tianyang L et al. summarized the current research status of hardware task dynamic scheduling based on the three basic elements of

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existing on-site programmable gate array processing: time, resources, and power consumption. The optimization effects of various scheduling methods were analyzed and evaluated from multiple dimensions. The research results indicated that the research could make a certain contribution to scheduling problems based on field programmable gate arrays [7]. Ye W et al. proposed a new unmanned aerial vehicle assisted edge computing system. The system dispatched edge nodes assisted by drones to provide communication and computational assistance for completing tasks generated by ground clients. Firstly, a trajectory design and task allocation problem were proposed, aiming to optimize the appropriate trajectory of each drone and schedule tasks for each ground client. A maximum drone trajectory and task allocation algorithm was proposed, which solved the task allocation problem by jointly optimizing the trajectory of the drone and the task scheduling of the ground client. The proposed method demonstrated good scheduling performance [8]. Wang et al. found that two-stage mixed flow workshop scheduling with batch machines and jobs arriving over time was complex and challenging. For online scheduling problems, traditional heuristic rules can quickly respond to dynamically arriving jobs, but their performance is poor and unstable. Therefore, a scheduling model based on the DQN algorithm was proposed. It transformed the online scheduling problem into a collaborative Markov decision process by defining the state space, action space, and reward function of different agents. The experimental results showed that the model could effectively combine online batch formation and scheduling, minimizing the total delay time [9]. Sun C et al. found that task scheduling and load balancing in heterogeneous computing environments received increasing attention in recent years. Therefore, a new task scheduling and load balancing method based on optimized deep reinforcement learning is proposed. This method first formulates the task scheduling problem into a Markov decision process. Then a dual deep Q-learning network was used to search for the optimal task allocation solution. The research results indicated that the proposed method model had shorter task response time and better load balancing effect [10].

In summary, many scholars have conducted research on task scheduling and achieved some results. In this study, a scheduling model based on Markov decision process is proposed, which applies DQN algorithm to DAG task scheduling. Then, to address the shortcomings of DQN algorithm, the PG algorithm is introduced to improve the model.

III. Big Data Task Scheduling Optimization Model Based on Deep Q-Network

The first section of this chapter provides an explanation for DAG task scheduling. The scheduling problem is optimized into a Markov decision model. A task scheduling algorithm based on DQN is proposed. In the second section, a PG algorithm is proposed to address the shortcomings of task scheduling algorithms based on DQN. Combined with the DQN algorithm, a scheduling model based on PG-DQN algorithm is proposed.

A. Directed Acyclic Graph Task Scheduling in Heterogeneous Environments

Cloud computing task scheduling refers to the rational allocation of tasks on cloud computing platforms to different computing resources, improving computing efficiency and resource utilization. Cloud computing servers usually have three parts, namely scheduling servers, work nodes, and data storage services. Performing computational tasks often requires the output of other tasks as input, which can be abstracted as a DAG representation. A DAG is a graph structure composed of nodes and directed edges. Each edge has a direction and there is no loop [11]. Starting from any node in the graph and following the direction of the directed edge, it will not return to that node. Its structure is shown in Fig. 1.

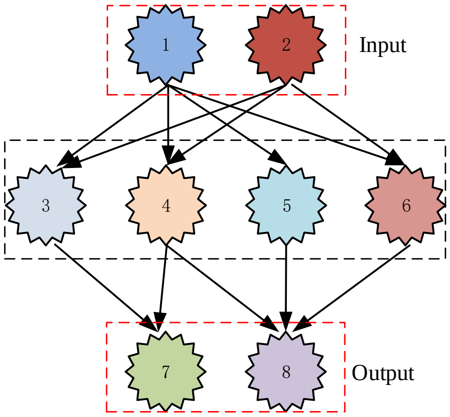


Fig. 1. DAG model diagram.

In Fig. 1, the node without a predecessor node task is the entry node, as shown in nodes 1 and 2 in the figure. There are no other nodes that rely on this node, such as node 7 and node 8. The computational cost of the task on each processor is shown in Eq. (1).

$$ECT_{V\times P}=\begin{bmatrix} ECT_{11} & \cdots & ECT_{1P} \\ \vdots & \ddots & \vdots \\ ECT_{V1} & \cdots & ECT_{VP} \end{bmatrix} \tag{1}$$

In Eq. (1), ECT represents the expected completion time. P refers to the computing node. V refers to the current task. The execution time is represented by the ECT matrix of $V\times P$, which is the time required to allocate each task to different nodes at the current moment [12]. In scheduling problems, the most common definitions are the earliest start time, earliest completion time, and maximum completion time. The earliest start time refers to the time when the task cannot start executing earlier than that, as shown in Eq. (2).

$$EST(v_i,p_j)=\max\left\{avail[j],\max_{v_k\in pred(v_i)}\{FT(v_k)+c_{k,i}\}\right\} \tag{2}$$

In Eq. (2), v_k represents the task. $FT(v_k)$ refers to the end time of the task execution. p_j represents a node. $avail[j]$ represents the earliest time used to calculate the node. $c_{k,i}$ represents the communication overhead between two tasks. When the direct precursor of a node is on the same processor as the node, the communication overhead between the two nodes can be considered as zero [13]. The earliest completion time indicates that the task cannot be completed earlier than that time, as shown in Eq. (3).

$$EFT(v_i, p_j) = EST(v_i, p_j) + \omega_{i,j} \tag{3}$$

In Eq. (3), $EST(v_i, p_j)$ refers to the earliest start time of the task. $\omega_{i,j}$ represents the time required for the task to perform calculations on the computing node. The earliest completion time is equivalent to the sum of the earliest start time and task execution time of the task [14]. The maximum completion time represents the time required to complete the last task in DAG, as displayed in Eq. (4).

$$Makespan = \max\{FT(v_{exit})\} \tag{4}$$

In Eq. (4), $Makespan$ represents the maximum completion time. v_{erit} represents the export task. The scheduling problem can be scheduled based on the execution time of the task. This process can be considered as a Markov decision process, which is a mathematical model used to describe stochastic decision problems. This method is based on an extension of Markov chain and decision theory. It is used to model sequential decision problems that include randomness and decision selection [15]. Its structure is shown in Fig. 2.

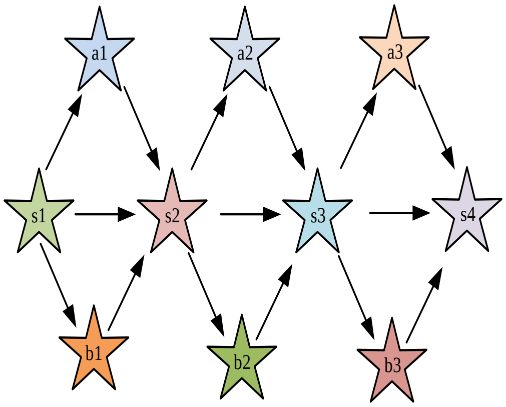


Fig. 2. Markov decision process.

From Fig. 2, the future state only depends on the current state and the currently selected action, rather than the past state and action. This nature makes the Markov decision process computable. Dynamic programming and other methods can be used to solve the optimal strategy [16-17]. The probability of a system transitioning from one state to another is defined as the state transition matrix, as shown in Eq. (5).

$$P = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & & \vdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix} \tag{5}$$

In Eq. (5), P represents the state transition matrix. The goal of Markov decision process is to find a strategy that maximizes long-term cumulative rewards. The quality of a strategy is measured by defining a value function. It represents the long-term cumulative reward that can be obtained by adopting a certain strategy in a certain state, as shown in Eq. (6).

$$G_t = R_{t+1} + \gamma R_{t+2} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \tag{6}$$

In Eq. (6), R_t represents the reward obtained from the environment after taking the action. t represents time. γ represents the attenuation factor, which reflects the future returns on the current value of the intelligent agent [18]. If the return is far from the current moment, the attenuation will be greater. To measure the value of a state, the expected cumulative reward is used as the state value, as displayed in Eq. (7).

$$v_\pi = E_\pi \left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \middle| S_t = s \right] \tag{7}$$

In Eq. (7), π represents the probability distribution of taking action. s represents the state. γ represents the attenuation factor. S represents the finite set state of the system. Based on the Markov decision process, a model is established for task scheduling problems in heterogeneous environments. The specific scheduling process is shown in Fig. 3.

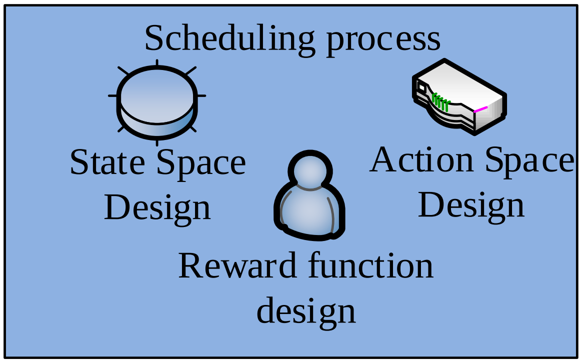


Fig. 3. Scheduling process.

The state space in a static environment is shown in Eq. (8).

$$S_t = [n, EST_1, \cdots, EST_M, T_{i,1}, \cdots, T_{i,M}] \tag{8}$$

In Eq. (8), t represents time. S_t represents the system state obtained by the scheduling model at t. M refers to the computing node. n refers to the current tasks. EST_j refers to the start time of the task in the processor. T represents the execution time. In task scheduling, the corresponding action space is shown in Eq. (9).

$$A_t = \{p_i \mid p_1, \cdots, p_M\} \tag{9}$$

In Eq. (9), A_t represents the action space. The model scheduling action at a certain moment is to schedule the current task to a computing node. The design of the reward function has significant impacts on the scheduling strategy. The designed reward function is shown in Eq. (10).

$$R_t = \max\{EST(v_i, p_j) \mid j = 1 \ldots q\} - \max\{EST(v_{i+1}, p_j) \mid j = 1 \ldots q\} \tag{10}$$

In Eq. (10), EST represents the start time of the task in the processor. In the Markov decision process, traditional methods lead to an extremely large state space, making modeling extremely slow and even impossible. Therefore, the reinforcement learning method is used to build models, which not only avoids the large state spaces, but also solves the continuous state spaces. DQN is used to build model. The core idea of DQN is to map the states and actions in the Markov decision process to a value function, namely the Q-value function. It is used to estimate the long-term return that can be obtained by taking an action in the current state. By learning this value function, DQN can select the optimal action in different states to maximize cumulative returns. DQN uses deep neural networks to approximate Q-value functions. The input of a neural network is a state. The output is an estimate of the Q-value for each action. After continuously adjusting the weights of the neural network, the estimation of Q value is closer to the true Q value. DQN uses an experience replay mechanism to train neural networks, which balances the sample correlation by saving and reusing previous experiences, improving training efficiency and stability.

The iterative process of the task scheduling algorithm based on DQN is as follows. Firstly, the set of tasks waiting for scheduling is inputted. The priority queue of the tasks is initialized. For tasks that meet the conditions, they will be arranged at the end of the queue. Secondly, the network parameters are initialized and weights are randomly generated. When there are tasks in the priority queue, the first task in the queue is selected as a pending scheduling task. Then the state is obtained. The action with the highest Q value is calculated. The task is scheduled to the corresponding computing node based on the action. Then, the return is calculated, and the DQN is backpropagated. Finally, the system status is updated.

B. Task Scheduling Optimization model Based on Deep Q-Network

The DQN algorithm has wide applicability and strong expressive ability. Combining deep learning with reinforcement learning, the DQN algorithm can be applied to various sequential decision problems, including game agent control, autonomous driving, robot path planning, etc. Therefore, it has high universality and flexibility. The DQN algorithm uses deep neural networks to approximate value functions, which can handle high-dimensional and complex state spaces [19]. Therefore, the DQN algorithm can provide better expressive power and performance when dealing with large-scale problems. The DQN algorithm combines deep learning and reinforcement learning, utilizing deep neural networks to learn the approximation of value functions. It can effectively deal with continuous state and action space problems, achieving good performance. The DQN algorithm uses experience replay and fixed target network methods to improve the sample utilization efficiency and training stability, avoiding the sample correlation and instability in traditional reinforcement learning methods.

However, the DQN algorithm model has some problems, such as the inability to represent random policies and difficulty in convergence. Therefore, the PG algorithm is adopted to improve the DQN algorithm. The PG algorithm is a method used to solve reinforcement learning problems by optimizing policy parameters to maximize cumulative rewards. Unlike traditional value function methods, the PG algorithm directly optimizes the policy function by using policy parameters as learnable parameters. The most commonly used method in PG algorithms is to use gradient ascent to update policy parameters. The core idea of the algorithm is to estimate the expected cumulative reward by sampling multiple trajectories. The gradient ascent method is used to update policy parameters to maximize expected rewards. To maximize cumulative rewards, a gradient ascent is applied to the cumulative rewards. The strategy function is shown in Eq. (11).

$$\pi(a \mid s, \theta) = P_r\{A_t = a \mid S_t = s, \theta_t = \theta\} \tag{11}$$

In Eq. (11), s represents the environmental state at time t. θ represents the model parameters. P_r represents the probability that a task is assigned to a computing node for execution. The task scheduling and model parameter optimization process is shown in Fig. 4.

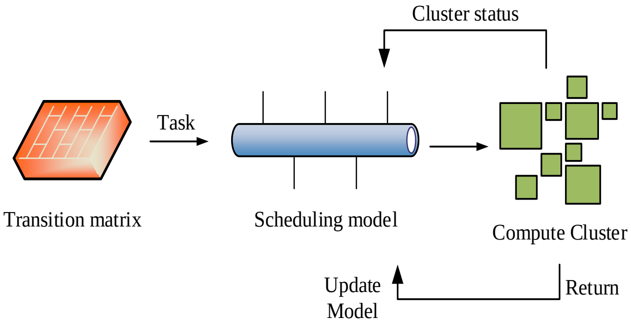


Fig. 4. Task scheduling and model parameter optimization process.

From Fig. 4, the scheduling model obtains a computing cluster through computing nodes. Then the computing cluster influences and updates the scheduling model through cluster status and returns [20]. For scheduling tasks, each task executes the above process to form a scheduling trajectory. The probability of generating scheduling trajectories is shown in Eq. (12).

$$P(\tau \mid \pi) = \rho_1(s_1) \prod_{t=0}^{T} P(s_{t+1} \mid s_t, a_t) \pi(a_t \mid s_t) \tag{12}$$

In Eq. (12), τ represents the scheduling trajectory. π represents the scheduling strategy. t represents the time step. The expected cumulative reward is shown in Eq. (13).

$$J(\pi_\theta) = \underset{\tau \sim \pi_\theta}{E}[R(\tau)] \tag{13}$$

In Eq. (13), $R(\tau)$ represents the cumulative reward. The training model needs to maximize the cumulative return. Therefore, the parameters are updated through the gradient ascent method. The iterative process based on PG is displayed in Fig. 5.

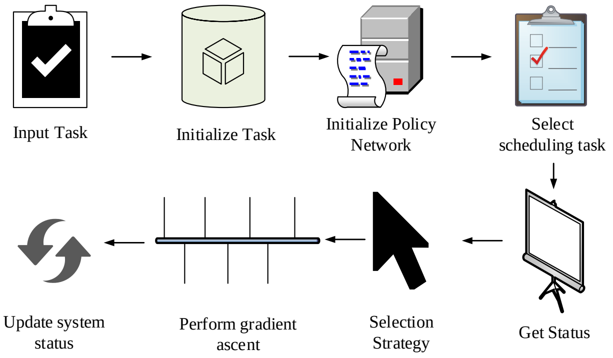


Fig. 5. The process of task scheduling algorithm based on PG.

In Fig. 5, the first step is to input a set of tasks waiting for scheduling, and initialize the priority queue of the tasks. For tasks that meet the conditions, they will be arranged at the end of the queue. Next, the policy network is initialized. If there are tasks in the priority queue, the first task in the queue is selected as a pending scheduling task. Then the state is obtained and the probability values for executing various scheduling actions are output. Based on the probability value, the current strategy action is selected. According to the policy action, the task is scheduled to the corresponding computing node. Then the reward of the scheduling action is calculated. Finally, the policy network is backpropagated and the system state is updated through the gradient ascent. The PG method is combined with the DQN algorithm to schedule tasks. The PG algorithm is responsible for outputting behavior, while the DQN algorithm evaluates behavior based on returns. Moreover, both the PG algorithm and the DQN algorithm simulate and update functions through neural networks. The combination of the two methods will result in better performance, as shown in Fig. 6.

In Fig. 6, all threads share a neural network, which includes the PG network and the DQN network. Each thread contains a neural network that is the same as the public network. Each network can be updated separately.

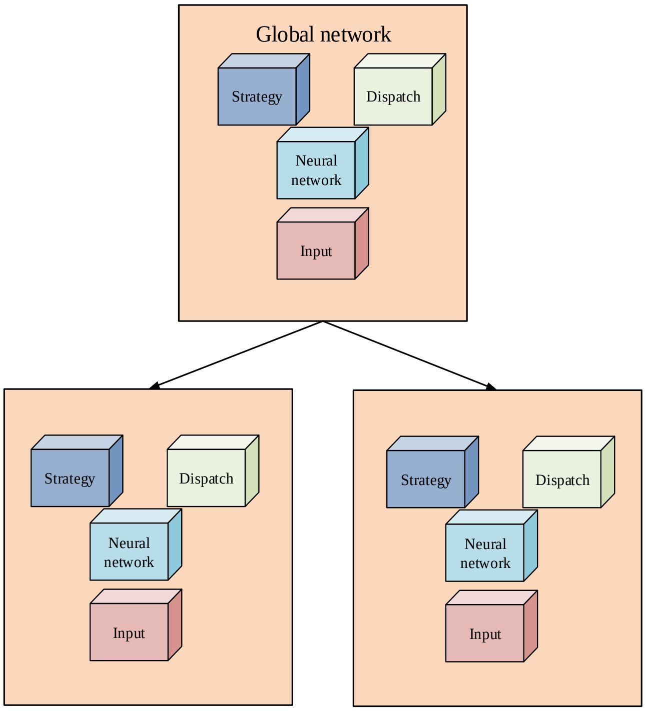


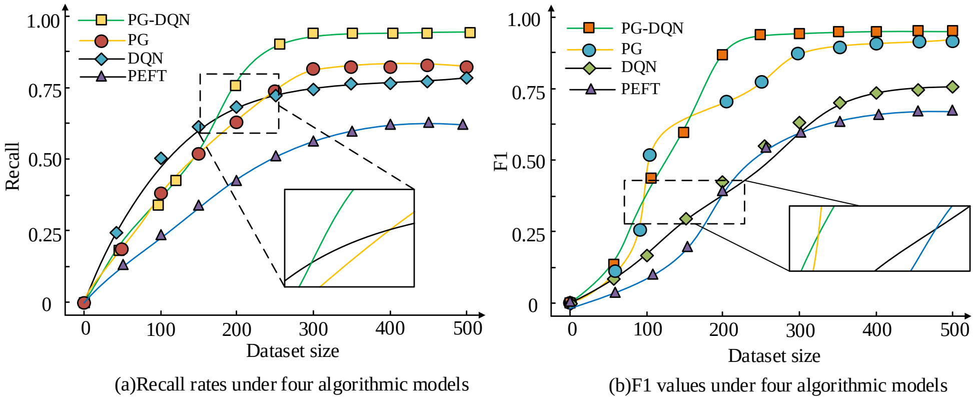
Fig. 6. PG-DQN network structure diagram.

IV. Performance Analysis of Big Data Task Scheduling Optimization Model based on Deep Q-Network

The first section of this chapter introduces the Predict Earliest Finish Time (PEFT) algorithm. It is compared with the proposed algorithm. Chapter 2 compares the cumulative rewards and the maximum completion time for dynamic scheduling models.

A. Performance Analysis of Static Task Scheduling Optimization Model based on Improved Deep Q-network

The operating system used in this experiment is Windows 10. The CUP is the Intel Core i7-4710MQ processor, with a main frequency of 2.5GHz and 8.00GB of memory. The estimated earliest completion time algorithm and PG algorithm are compared with the algorithm used in this study [21-22]. The result is shown in Fig. 7.



(a)Recall rates under four algorithmic models

(b)F1 values under four algorithmic models

Fig. 7. Recall rates and F1 values of four methods.

Fig. 7(a) shows the recall rates of four algorithms on different datasets. Fig. 7(b) displays the F1 values of four algorithms on different datasets. In Fig. 7(a), the recall rates of the four models all increased with the increase of the training set. The proposed PG-DQN algorithm performed well among the four methods. When the dataset size was around 500, the recall rates of PG-DQN, PG, DQN, and PEFT were 0.96, 0.83, 0.79, and 0.63. In Fig. 7(b), the F1 values continued to increase with the increase of the training set. When the dataset size was 500, the F1 values of the four algorithms were 0.97, 0.90, 0.76, and 0.65, respectively. The proposed PG-DQN exhibits good performance in terms of recall and F1 value among the four models. Moreover, the PG-DQN has good performance on smaller datasets. The scheduling length ratio in the scheduling task is used as an indicator for comparison. Fig. 8 displays the results.

In Fig. 8, compared with the traditional PEFT, DQN and PG had a smaller scheduling length ratio. The proposed PG-DQN had a smaller scheduling length ratio than the other three algorithms when scheduling 200-1000 tasks. The PG-DQN can explore more reward actions. The proposed PG-DQN algorithm performs well. It can still maintain good performance in multiple tasks. The training time and scheduling time are compared. Fig. 9 displays the results.

Fig. 9 (a) shows the training time on different datasets and Fig. 9(b) presents the processing time of the algorithm under different task quantities. From Fig. 9(a), the FEPT exhibited longer training time under different dataset sizes. The training time of the PG-DQN was slightly longer than that of the PG and slightly shorter than that of the DQN. This is because the proposed algorithm model is a hybrid model of two methods, resulting in a more complex structure and more calculated parameters. In Fig. 9(b), the proposed PG-DQN only had slightly higher processing time than the PG in various quantities of task scheduling. Although the proposed PG-DQN does not take the least time, considering the scheduling performance, the overall performance of the PG-DQN is still better.

B. *Performance Analysis of Dynamic Task Scheduling Optimization model based on Improved Deep Q-network*

The experiment randomly generates 100 DAG tasks, each containing 10 sub-tasks, which are used as the dataset. The result is shown in Fig. 10.

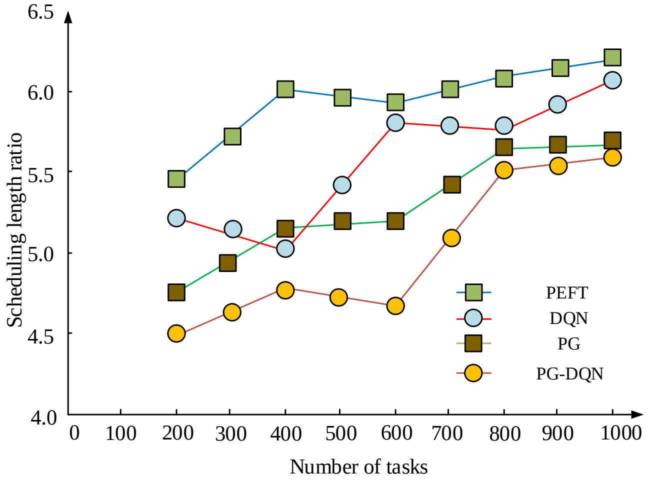
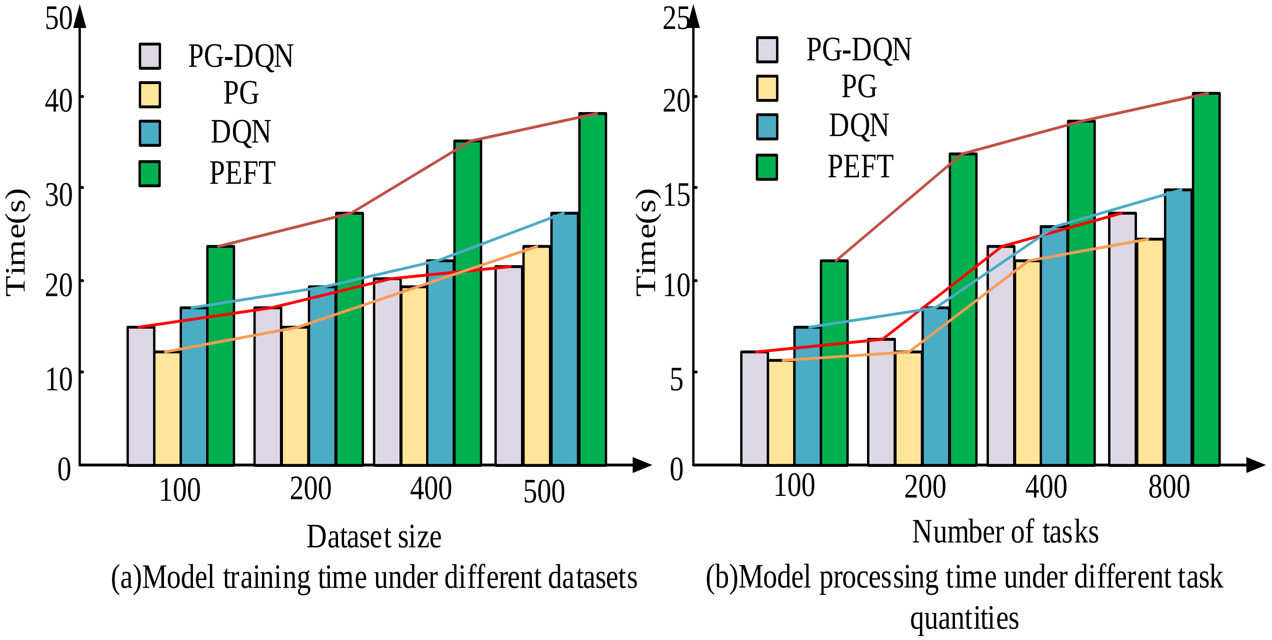


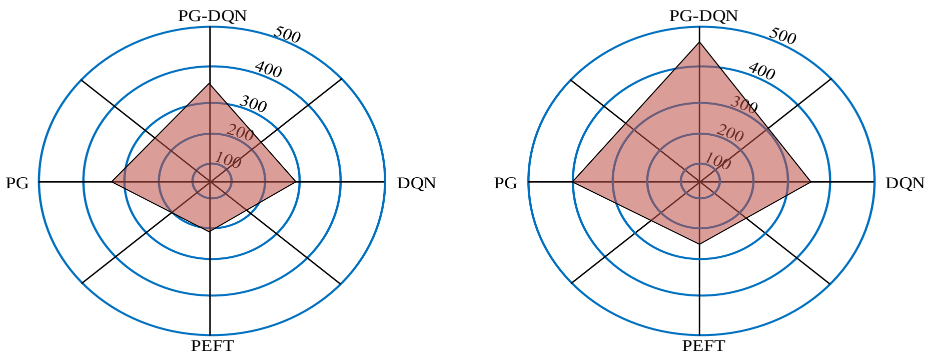
Fig. 8. The relationship between the scheduling length ratio index of different algorithms and the number of tasks.



(a)Model training time under different datasets

(b)Model processing time under different task quantities

Fig. 9. Calculation time required for scheduling different algorithms.



(a) Cumulative rewards for different task scheduling algorithms with 100 iterations

(b) Cumulative rewards for different task scheduling algorithms with 500 iterations

Fig. 10. Cumulative rewards of task scheduling algorithm under different iterations.

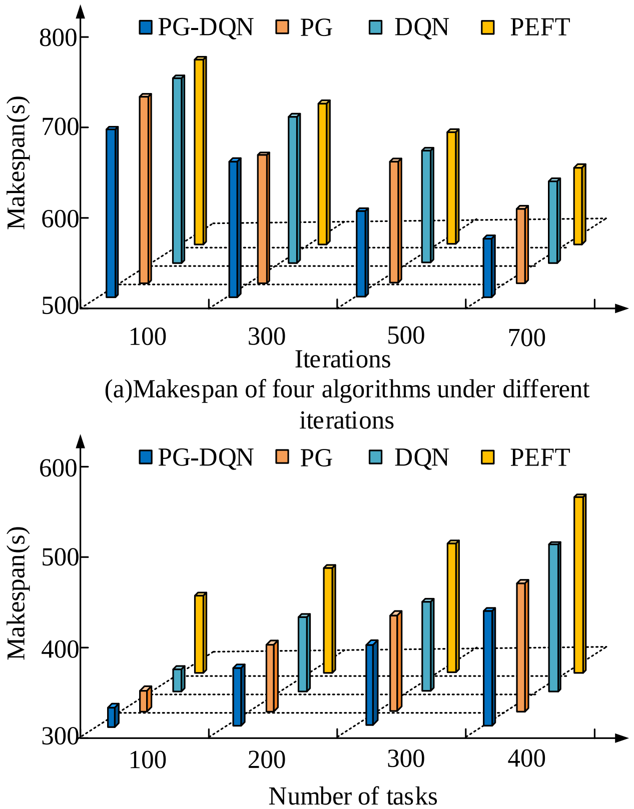
Fig. 10(a) presents the cumulative rewards of different task scheduling algorithms at 100 iterations. Fig. 10(b) displays the cumulative rewards of different task scheduling algorithms at 500 iterations. In Fig. 10(a), at 100 iterations, the cumulative reward for the PG-DQN, PG, DQN, and PEFT were 350, 320, 290, and 210, respectively. In Figure 10 (b), at 500 iterations, the cumulative reward for the PG-DQN, PG, DQN, and PEFT were 460, 400, 350, and 260, respectively. The cumulative return of the model is lower when the number of iterations is small. After reaching 500 iterations, the cumulative return of the model is good. The proposed PG-DQN has the highest cumulative return among the four models, indicating that the PG-DQN has good performance. The maximum completion time is compared, as displayed in Fig. 11.

Fig. 11(a) displays the maximum completion time at different iterations. Fig. 11(b) displays the maximum completion time at different task quantities. According to Fig. 11 (a), when the number of iterations was 100, 300, 500, and 700, the maximum completion time of PG-DQN was 723s, 654s, 591s, and 576s, respectively, which were lower than the other three algorithm models. In Fig. 11(b), when the scheduling tasks were 100, 200, 300, and 400, the maximum completion time of PG-DQN was 342s, 387s, 410 s, and 442s, respectively. The proposed algorithm model has good model performance at different iterations and task quantities. 50 users are randomly selected and divided into an average of five groups to rate the model, as shown in Table I.

According to Table I, the scores of the five groups on the PG-DQN were 84.4, 97.2, 92.5, 94.7, and 90.1, respectively. The scores for the PG were 80.2, 94.5, 90.4, 90.6, and 86.5, respectively. The scores for the DQN were 78.6, 80.7, 85.4, 87.6, and 82.4, respectively. The scores for the PEFT were 76.8, 78.3, 82.4, 86.1, and 78.1. The PG-DQN has better scores among the four models, which has received widespread praise.

TABLE I. USER EVALUATION FORM

/	Group 1	Group 2	Group 3	Group 4	Group 5
PG-DQN	84.4	97.2	92.5	94.7	90.1
PG	80.2	94.5	90.4	90.6	86.5
DQN	78.6	80.7	85.4	87.6	82.4
PEFT	76.8	78.3	82.4	86.1	78.1



(a)Makespan of four algorithms under different iterations

(b)Makespan of four algorithms under different task quantities

Fig. 11. Comparison of maximum completion time for tasks.

V. Conclusion

The task scheduling algorithm has significant value for the platform operation efficiency. A scheduling model based on Markov decision process is proposed, which applies DQN algorithm to DAG task scheduling. Then, to address the shortcomings of DQN algorithm, the PG algorithm is introduced to improve the model. According to the results, the recall rates of the four models increased with the increase of the training set. When the dataset size was around 500, the recall rates of the PG-DQN, PG, DQN, and PEFT were 0.96, 0.83, 0.79, and 0.63. The F1 values of the four algorithms were 0.97, 0.90, 0.76, and 0.65. Under different dataset sizes, the training time of the PG-DQN was slightly longer than that of the PG and slightly shorter than that of the DQN. In various task scheduling quantities, the proposed PG-DQN only had slightly higher processing time than the PG. At 100 iterations, the cumulative reward for the PG-DQN, PG, DQN, and PEFT were 350, 320, 290, and 210, respectively. At 500 iterations, the cumulative reward for the PG-DQN, PG, DQN, and PEFT were 460, 400, 350, and 260, respectively. The proposed method has good scheduling performance. However, there are also shortcomings in the research. The study only considers the execution time prediction for single threaded tasks. Future research will be conducted on multi-threaded tasks. For the task scheduling model, in the future, parameters will be adjusted based on the existing foundation. The model structure will continue to be optimized to achieve better scheduling results. The model architecture will also be considered for multi-objective optimization, such as fairness between tasks and priority scheduling of tasks.

VI. Discussion

The scheduling model is a model established for scheduling problems. This study proposes a scheduling model based on Markov decision process, which applies the DQN algorithm to DAG task scheduling. Then, to address the shortcomings of the DQN algorithm, a PG algorithm is introduced to combine it and improve the model. The experimental results showed that the DQN algorithm had a smaller scheduling length ratio compared with the traditional PEFT algorithm and PG algorithm. The proposed PG-DQN algorithm had a smaller scheduling length ratio than the other three algorithm models when scheduling 200-1000 tasks, indicating that the PG-DQN algorithm model can explore more rewarding actions. Under different dataset sizes, the FEPT algorithm exhibits longer training times. The training time of PG-DQN algorithm model was slightly longer than that of PG algorithm and slightly shorter than that of DQN algorithm. This is because the proposed algorithm is a hybrid model of two methods, resulting in a more complex structure and more calculated parameters. When the number of iterations were 100, 300, 500, and 700, the maximum completion time of PG-DQN was 723s, 654s, 591s, and 576s, respectively, which were lower than the other three models. When the scheduling tasks were 100, 200, 300, and 400, the maximum completion time of PG-DQN was 342s, 387s, 410 s, and 442s, respectively. The research results indicated that the proposed method model has better performance and efficiency.

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Conflict of Interest

The authors have no relevant financial or non-financial interests to disclose.

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