Beyond the Norm: A Modified VGG-16 Model for COVID-19 Detection

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***Abstract*—The outbreak of Coronavirus Disease 2019 (COVID-19) in the initial days of December 2019 has severely harmed human health and the world's overall condition. There are currently five million instances that have been confirmed, and the unique virus is continuing spreading quickly throughout the entire world. The manual Reverse Transcription-Polymerase Chain Reaction (RT-PCR) test is time-consuming and difficult, and many hospitals throughout the world do not yet have an adequate number of testing kits. Designing an automated and early diagnosis system that can deliver quick decisions and significantly lower diagnosis error is therefore crucial. Recent advances in emerging Deep Learning (DL) algorithms and emerging Artificial Intelligence (AI) approaches have made the chest X-ray images a viable option for early COVID-19 screening. For visual image analysis, CNNs are the most often utilized class of deep learning neural networks. At the core of CNN is a multi-layered neural network that offers solutions, particularly for the analysis, classification, and recognition of videos and images. This paper proposes a modified VGG-16 model for detection of COVID-19 infection from chest X-ray images. The analysis has been made among the model by considering some important parameters such as accuracy, precision and recall. The model has been validated on publicly available chest X-ray images. The best performance is obtained by the proposed model with an accuracy of 97.94%.**

Keywords*—*Covid-19; coronavirus; artificial intelligence; deep learning; transfer learning; VGG-16; performance metrics

I. Introduction

Since the beginning of December 2019, the Coronavirus Disease 2019 (COVID-19) outbreak has put enormous pressure on the entire world [1]. According to the World Health Organization (WHO), more than five million people have been infected globally to date, and there have been about three lakh confirmed cases of death. A respiratory disease, COVID-19 is brought on by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) and is characterized by symptoms such as fever, myalgia, dry cough, headache, sore throat, and chest pain [2]. The infected person may not exhibit all symptoms for up to 14 days.

A severe respiratory condition known as COVID-19 can be cured without the use of antibiotics in affected individuals. Chronic medical diseases like diabetes, chronic respiratory illnesses, and cardiovascular issues increase the chance of spreading this virus. According to the WHO, the COVID-19 symptoms, which include fever, tiredness, a dry cough, shortness of breath, aches, pains, and sore throat, are similar to those of the ordinary flu [3]. Because of these common symptoms, it is difficult to detect the virus in its early stages. There is no chance that antibiotics, which are used to treat bacterial or fungal infections, will be able to halt this as it is a virus.

In medical, scientific, and healthcare laboratories, the coronavirus has been identified using a variety of diagnostic techniques. Indirect methods evaluate antibodies against the virus in a host that has been exposed, whereas direct tests identify the contamination directly by detecting the viral RNA. During a pandemic, a clinical test method should be accurate and sensitive enough to quickly make the right clinical recommendations. The various diagnostic methods for the covid-19 detection are shown in Fig. 1.

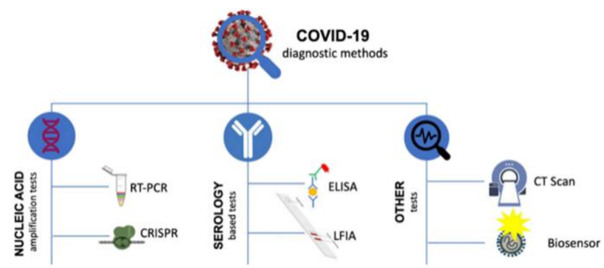

Fig. 1. Diagnostic method for Covid-19 detection [4].

The most dependable and popular technique for COVID-19 detection among the several methods available is RT-PCR [5]. There is sometimes a lack of supplies during pandemic events, including PCR kits. Therefore, having a variety of diagnostic method choices is crucial. Equally crucial are other testing methods and accessories that may be produced locally, even on a small scale. Those platforms would be suitable in environments with restricted resources as well. Because the currently used RT-PCR techniques are expensive, many nations, especially those with poor incomes, cannot afford enough COVID-19 tests to screen a broader population. Screening asymptomatic people throughout the incubation phase still has significant gaps. It is also difficult to accurately predict live virus shedding in healed patients in order to make de-isolation decisions. Several COVID-19 test kits have been recalled in various nations due to questionable quality. The rigorous evaluation of the diagnostic precision of the recently introduced SARS-CoV-2 assays is hampered by the lack of a recognized reference standard, the use of various sample collection and preparation techniques, and a flawed understanding of viral interplay across the time phase of infection.

There is currently no specific medication or treatment for this illness. However, RT-PCR is the technique that is most frequently used to diagnose COVID-19. It has recently been discovered that medical imaging methods like X-rays and Computed Tomography (CT) are essential for testing COVID-19 instances. The chest radiography images (chest X-ray or CT images) have been extensively investigated since the virus typically infects the lungs [6]. Radiologists manually evaluate these images to look for any visual signs of COVID-19 infection. These visual cues can be used as an alternative screening technique for infected patients.

The WHO has approved the RT-PCR technique as a coronavirus testing method, in which short DNA or RNA sequences are evaluated and replicated or amplified. But it takes more than one test to totally rule out coronavirus in some people. WHO guidelines for laboratory testing state that negative results do not necessarily rule out the possibility that the person is virus-infected. The lack of screening workstations and testing kits to identify COVID-19 makes it incredibly challenging for medical staff and professionals to address the issue. It is incredibly challenging for medical practitioners in this situation to promptly and precisely detect possible COVID-19 cases. Numerous tests are also necessary because of the cases' exponential growth in order to fully comprehend the circumstances and come up with the finest decisions.

Despite the availability of numerous imaging modalities, chest radiography is believed to have a low sensitivity for major clinical findings. Doctors frequently use X-ray imaging technologies to identify pneumonia because they are an essential part of healthcare systems all over the world. The use of chest X-ray equipment is time-consuming in the absence of screening workbenches and kits notwithstanding their simplicity in locating COVID-19 cases. Additionally, there may be situations where individuals receive imaging for a different reason and the results of their scans point to COVID-19. The findings from the chest X-ray images strongly suggest that even in the early stages of COVID-19, the effect can be seen in the lungs, particularly in the lower lobes and posterior segments, with peripheral and subpleural distribution. The lesions diffuse more and more as time passes. The biggest problem, though, is that analyzing each chest X-ray image and determining what information is most important takes a lot of time and the presence of medical professionals. Therefore, to assist in the detection of COVID-19 cases using chest X-ray images, medical personnel need computer assistance.

Although the traditional diagnosing process has sped up somewhat, it still puts medical professionals at great risk. Additionally, it is expensive, and there are only a few diagnostic test kits available. On the other hand, screening based on medical imaging techniques (such X-ray and CT) is often safe, quick, and available. X-ray imaging, as opposed to CT imaging, has been utilized extensively for COVID-19 screening because it is less expensive, requires less imaging time, and is more readily accessible even in rural areas than CT imaging. The larger-scale visual examination of X-ray images by radiologists is time-consuming, labor-intensive, and could result in an incorrect diagnosis because of ignorance of the virus-infected regions. Therefore, the development of automated approaches to acquire a quicker and more precise COVID-19 diagnosis is highly necessary. The most recent automated methods sought to lessen the labor of radiologists while enhancing the power of X-ray imaging using cutting-edge Artificial Intelligence (AI) technologies [7]. Convolutional Neural Networks (CNN), a type of DL model, in particular, have proven to be more efficient than conventional AI techniques and are frequently used to analyze a variety of medical images. CNN has recently been used to successfully identify COVID-19 in chest X-ray images. The major contribution of this paper includes:

- An effective detection model for Covid-19.
- A modified VGG-16 model for Covid-19 detection from chest X-ray images.
- Classification of chest X-ray images into Covid-19 and Normal.

This paper seems to have the following format. The details of the currently used COVID-19 detection techniques are covered in Section II. The methodology is covered in Section III. The experimental findings and conclusions are presented in Sections IV and V respectively. Finally, the future works are presented in Section VI.

II. Literature Review

Saul Calderon-Ramirez et al. [8] introduced COVID-19 detection from chest X-ray images using semi- supervised deep learning methods. Using a semi-supervised deep learning framework built on the Mix Match architecture, chest X-rays are classified into Covid-19, pneumonia, and healthy cases in this paper. When there is a lack of high-quality labeled data, performance levels for Covid-19 identification can be enhanced with the use of the semi-supervised framework. Shamima Akter et al. [9] introduced COVID-19 detection using deep learning approaches. The paper suggested a deep learning-based automated classification model based on a convolutional neural network that exhibits a high COVID-19 detection rate. The COVID-19 symptoms were initially identified utilizing the dataset by applying eleven pre-existing CNN models. A confusion matrix was used to demonstrate how well the models performed. Zehra Karhan and Fuat Akal [10] discussed Covid-19 Classification Using Deep Learning in Chest X-Ray Images. The ResNet50 model was utilized for Covid-19 classification from chest X-ray images. Artificial intelligence allows for fast analysis of chest X-ray images and identification of diseased individuals. It can also be applied when RT-PCR testing and other options are insufficient. Sami Bourouis et al. [11] introduced Bayesian Learning of Shifted-Scaled Dirichlet Mixture Models for Covid-19 detection. In order to distinguish between individuals who are either negative or positive for particular types of viruses and pneumonia, this research introduced a novel statistical framework. The success and reliability of this mixing model in recent image processing applications is encouraging. The established Bayesian framework has the benefit of accounting for uncertainty to precisely estimate the model parameters and the capability to address the overfitting issue. Lightweight deep learning models for detecting COVID-19 from chest X-ray images were discussed by Stefanos Karakanis and Georgios Leontidis [12]. In this paper, a new approach was proposed to detect COVID-19 via exploiting a conditional generative adversarial network to generate synthetic images for augmenting the limited amount of data available. The study focused on both binary classification for COVID-19 vs Normal cases and multi-classification that includes a third class for bacterial pneumonia.

In study [13], Covid-19 detection using majority voting classifiers are used. This work introduced an automated COVID screening (ACoS) method that identifies healthy, suspicious, and COVID-19-infected patients using radiomic texture descriptors taken from CXR images. The proposed system employs a majority vote-based classifier ensemble comprising five benchmark supervised classification algorithms in a two-phase classification approach (normal vs. abnormal and COVID-19 vs. pneumonia). Tulin Ozturk et al. The study in [14] proposed an automated detection of COVID-19 cases using deep neural networks with X-ray images. This paper presented a new model for automatically detecting COVID-19 from raw chest X-ray images. The suggested approach is designed to deliver precise diagnostics for multi-class classification and binary classification. The DarkNet model was used as a classifier for the real-time You Only Look Once (YOLO) object identification system. Improving the performance of CNN to predict the likelihood of COVID-19 using chest X-ray images with preprocessing algorithms was proposed by Morteza Heidari et al. [15]. The purpose of this study is to create and evaluate a new computer-aided diagnostic method using chest X-ray images to identify pneumonia caused by the coronavirus. A histogram equalization technique and a bilateral low-pass filter are used to process the original image in the first two image preparation steps of the CAD method. Then, a pseudo-color image is created using the original image, two filtered images, and the original image. This image is fed into three input channels of a transfer learning-based convolutional neural network (CNN) model. Muhammad Ilyas et al. [16] discussed various methods used for Covid-19 detection using Artificial Intelligence. This paper outlines the difficulties we are now encountering as well as the various methods utilized to detect COVID-19. To stop the spread of the virus through contact, an automatic detection system must be created. For the detection of COVID-19, a number of deep learning architectures, including ResNet, Inception, Googlenet, etc., are being used. In [17], proposed an automatic Covid-19 detection method. To assess and contrast the created models, three distinct experiments are conducted in accordance with three preprocessing approaches. The objective is to assess the effects of data preprocessing on the outcomes and how well they can be explained. Similarly, a critical evaluation of various variability issues that could threaten the system and its impacts is carried out.

Shayan Hassantabar et al. [18] proposed a diagnosis and detection of infected tissue of COVID-19 patients based on lung X-ray image using convolutional neural network approaches. Three deep learning-based techniques were employed in this study to identify and diagnose COVID-19 patients using X-ray images of the lungs. A convolutional neural network (CNN) technique was introduced, which uses the lung images and deep neural network (DNN) methods based on the fractal characteristic of images, for the diagnosis of the condition. In study [19], an automatic detection of COVID-19 infection using chest X-Ray images through transfer learning was proposed. It employs various convolutional neural network (CNN) architectures that have been trained on ImageNet and modifies them to function as feature extractors for the X-ray images. Then, the CNNs are integrated with consolidated machine learning techniques, including support vector machine, k-Nearest Neighbor, Bayes, Random Forest, and multilayer perceptron (MLP). Govardhan Jain et al. [20] proposed a deep learning approach to detect Covid-19 coronavirus with X-Ray images. Using accessible resources and cutting-edge deep learning techniques, an alternative diagnostic tool to find COVID-19 patients is suggested in this work. The proposed approach is put into practice in four stages: data augmentation, preprocessing, creating stage-I and stage-II deep network models. In order to improve the generalization of the model and avoid the model from overfitting, this work used web resources of 1215 images that have been improved further by data augmentation techniques, bringing the total number of images in the dataset to 1832. Aras M. Ismael and Abdulkadir Şengür [21] introduced deep learning based covid-19 detection method. In order to categorize COVID-19 and normal (healthy) chest X-ray images, deep-learning-based approaches, including deep feature extraction, fine-tuning of pretrained convolutional neural networks (CNN), and end-to-end training of a constructed CNN model, have been used in this study. Pretrained deep CNN models (ResNet18, ResNet50, ResNet101, VGG16, and VGG19) were utilized for deep feature extraction. The Support Vector Machines (SVM) classifier was used to categorize the deep features using a variety of kernel functions, including linear, quadratic, cubic, and gaussian. The fine-tuning process also made use of the previously mentioned pre-trained deep CNN models. In [22], a novel CNN model called CoroDet for automatic detection of COVID-19 by using raw chest X-ray and CT scan images has been proposed. With the development of CoroDet, an accurate diagnostic tool for COVID and Normal, COVID, Normal, and Non-COVID Pneumonia, and 4 Class Classification was available (COVID, Normal, non-COVID viral pneumonia, and non-COVID bacterial pneumonia).

While deep learning methodologies and chest X-ray images have been widely employed in COVID-19 detection research, there remains a crucial requirement to evaluate the adaptability and resilience of these models across diverse imaging scenarios and population demographics. The absence of investigations into real-world variables, including demographic variances, imaging device fluctuations, and variations in data acquisition settings, raises legitimate concerns about the external reliability and validity of existing models. This underscores the urgency for more comprehensive and interdisciplinary research endeavors to enhance the practicality of these diagnostic tools.

The block diagram of the proposed method is given in Fig. 2. The proposed method is carried out using COVID-19 X-ray Dataset [23]. The dataset contains two folders: test and train. The dataset includes NORMAL and COVID-19 images with .jpg format. The models are trained and tested using the complete dataset. 30% of the dataset's data were used for testing, and the remaining 70% were used for training. The input images are preprocessed before applying to the pretrained model. In order to ensure numerical stability in CNN systems, normalization of data is a crucial step. Normalization increases the likelihood that a CNN model will learn more quickly and that the gradient descent will be stable. As a result, in this study, the input image pixel values have been normalized to fall between 0 and 1. The grayscale images used in the datasets under consideration were rescaled by multiplying the pixel values by 1/255. The CNN models have demonstrated to perform better on larger datasets and need a significant amount of data for optimal training. The dataset only contains a very small number of training X-ray images. Since it is difficult to gather medical data, this has been a major concern when doing analysis of medical images using DL algorithms. Data augmentation approaches, which enable to increase the number of images via a set of modifications while keeping class labels, have been frequently used to address this issue. Additionally, augmentation makes the images more variable and acts as a dataset. The preprocessing includes normalization and augmentation. The preprocessed images are used to train the modified VGG-16 model. Finally, the model classifies the chest X-ray images. The sample and augmented chest X-ray images are shown in Fig. 3 and Fig. 4 respectively.

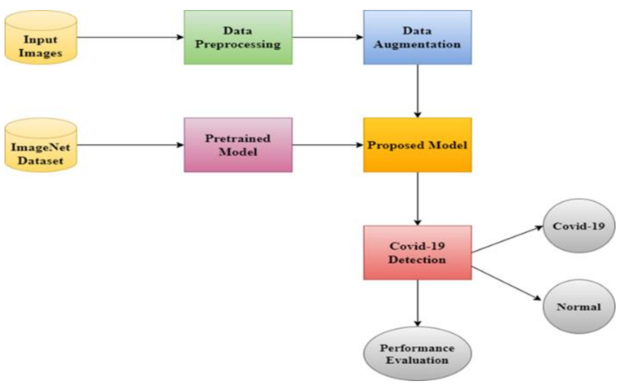

Fig. 2. Block diagram of the proposed method.

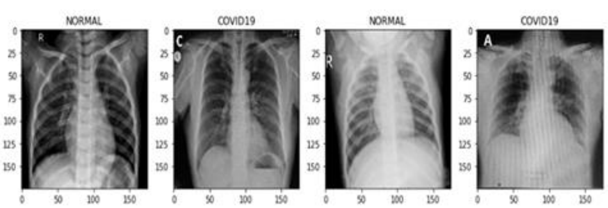

Fig. 3. Sample CXR images.

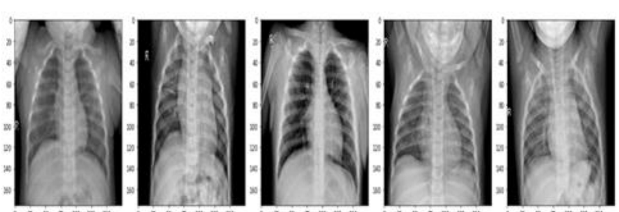

Fig. 4. Augmented CXR images.

III. METHODOLOGY

For the study of visual images, CNNs are the most widely used class of neural networks in deep learning. A multi-layered neural network that provides solutions, notably for the analysis, classification, and recognition of images and videos, is the fundamental aspect of CNN. CNN is made up of different layers. They are the convolution layer, the pooling layer and the fully connected layer. In essence, the convolutional and pooling layers provide the model's learning while the full connection layer handles categorization. The convolutional layer is the central part of CNN architectures. The feature map is created by applying high- and low-level filters to the input image. The pooling layer is often positioned between the convoluted layers. Its main objective is to reduce the size of the feature map in order to reduce the amount of computational resources required to construct the model. It also efficiently trains the model by removing its dominating and invariant characteristics. Although there are many different pooling methods, the maximum and average pooling layers are the most often used ones. Each neuron in the entire connection layer is connected to every neuron from the layer above. Depending on its topology, CNN architecture may have fewer or more complete connection layers. The output layer comes after the last full connection layer. It is now possible to create output distributions using SoftMax regression by obtaining probability distributions for the output classes in classification experiments.

Transfer learning is a machine learning method that applies knowledge that a CNN has learned from a batch of related data to a separate but related problem. The fundamental element of transfer learning is that knowledge can be acquired by transferring it from one related task to another. With pretrained models, the transfer learning design method is widely applied. These pretrained models are based on deep convolutional neural networks. Initial CNN training for a classification problem using sizable training datasets is required for this deep learning technique. Since a CNN model can learn to extract significant components of the image, the availability of data for initial training is a vital element of efficient training.

A. VGG-16

The Visual Geometric Group (VGG) Network is a simple model. Its integration with CNN models is common due to its deeper structure, which is followed by layers of associated double- or triple-convolution layers, which is the most noticeable difference between it and prior models. The model architecture is given in Fig. 5. It is possible to utilize the model to extract pertinent features from suitable new images. The ImageNet dataset has the ability to extract attributes from images, including brand-new ones that might not yet exist or that might be found in dataset categories that are completely unrelated to one another [24]. Therefore, it is advantageous to use pretrained models as effective feature removers.

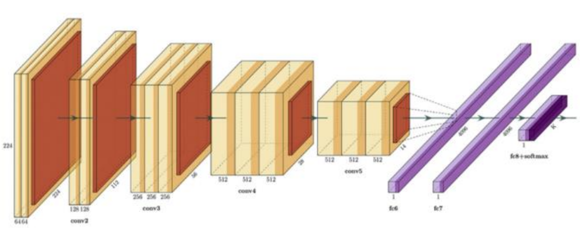

Fig. 5. VGG-16 architecture.

The VGG16 design uses three convolution filters with a total of 13 convolution layers for feature extraction. Each ReLU layer has a maximum pooling layer for sampling and is followed by a convolution layer. Its final classification layer is composed of 1000 units that are equivalent to the image categories in the ImageNet database, and it has three fully connected classification layers, two of which are hidden layers. This design simulates a larger filter while maintaining the benefits of smaller filter sizes. VggNet has been shown to perform better with fewer parameters. Furthermore, two ReLU layers rather than only one were used for the two convolution layers. The depth of the volumes increases as the number of filters increases since the convolution and partnering layers reduce the spatial size of the input volumes in each layer.

B. Modified VGG-16

The modified VGG-16 design reduces the number of parameters by decreasing the network depth in contrast to the original VGG-16 architecture in order to avoid problems with under and overfitting during training. The original architecture of the VGG16 convolutional network was preserved by doing feature extraction with two consecutive small convolutional kernels as opposed to a single large one. This expedites training while retaining the depth of the network by reducing the number of parameters while maintaining the VGG16 perceptual effects.

The input image size was altered initially, after which the hidden layer was divided into five blocks, each of which contained two convolutional layers and a pooling layer. Using 32 randomly generated 3x3 convolutional kernels, each convolutional layer extracted features, while the pooling layer compressed the image. Convolutional kernels in blocks 3 through 5 were all the same size (3x3), but there were, respectively, 64, 128, and 64 kernels in each block. When compared to VGG16, the number of parameters needed was decreased by decreasing the convolutional kernels. After that, the pooling layer reduced the size of the image, the flattened layer reduced feature mappings to one dimension, and three fully connected layers combined output features into two classes. Finally, the performance of the model is evaluated based on different metrics.

C. Performance Evaluation

Accuracy is one of the measures that is most frequently used while classifying data. Accuracy is a parameter measuring how well a model performs across all classes. When all classes are treated equally, it is advantageous. It is calculated by dividing the total number of predictions by the number of predictions that came true. The formula below can be used to assess a model's accuracy.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

The ratio of Positive samples that were correctly identified is used to calculate precision. How precisely the model can classify a sample as positive depends on its precision. The capacity to correctly classify all positive samples as positive while avoiding incorrectly labeling a negative sample as positive is known as precision.

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

By dividing the total number of Positive samples by the recall rate, the percentage of Positive samples that were correctly identified as Positive is obtained. Recall quantifies how well a model can find Positive samples. The recall increases as more positive samples are found.

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

IV. RESULTS AND DISCUSSION

A. Hardware and Software Setup

The system consists of a single NVIDIA GeForce GTX 1080 Ti GPU 2760 4MB, an Intel Core i7-6850K 12-core processor operating at 3.60 GHz, and additional parts. Google Collaboratory serves as the testing and training platform. The hyperparameters utilized for this study are tabulated in Table I.

TABLE I. HYPERPARAMETERS

Batch Size	32
Activation Function	ReLu
Optimizer	Adam
Loss Function	Binary Crossentropy

B. Experimrntal Results

In Table II, classification report for the modified VGG-16 model is tabulated. The model's precision, recall, and accuracy are 97.94%, 98.23%, and 95.58%, respectively.

Fig. 6 shows a plot of the modified VGG-16 model's accuracy. As the number of epochs increases, training and testing accuracy constantly improves.

Fig. 7 displays the modified VGG-16 model's loss. With more epochs, the training and testing loss always decreases.

TABLE II. CLASSIFICATION REPORT OF PROPOSED MODEL

Parameters	Obtained Results
Accuracy	97.94 %
Precision	98.23 %
Recall	95.58 %

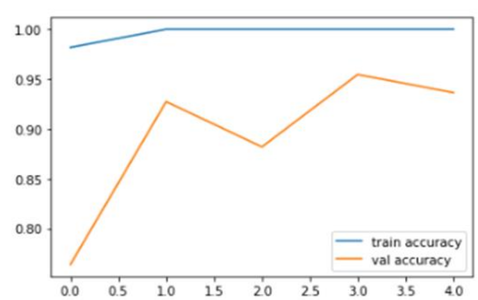

Fig. 6. Accuracy plot of proposed model.

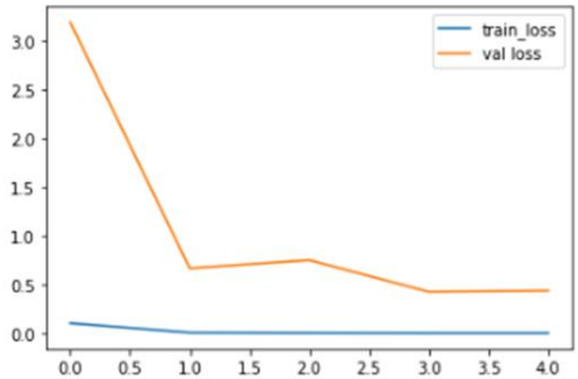

Fig. 7. Loss plot of proposed model.

A graph between numerous possible learning rates and the validation loss has been plotted in order to discover the learning rate for the model. The plot between learning rate and loss obtained for the model is shown below. The learning rate is a hyperparameter that determines how much to alter the model each time when model weights are updated in response to the predicted error. The plot between learning rate and loss of the model is illustrated in Fig. 8.

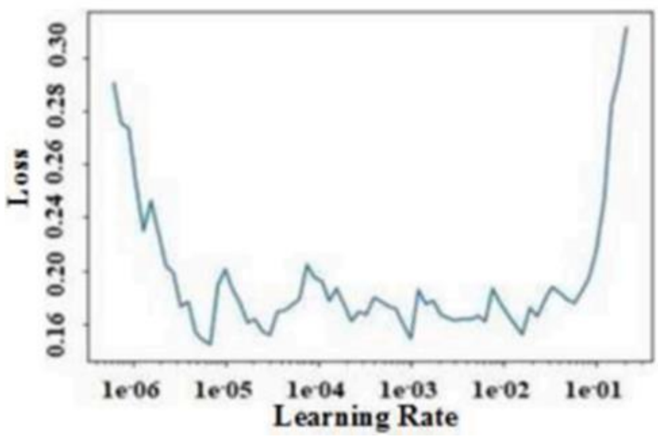

Fig. 8. Plot between learning rate and loss of the model.

It can be difficult to choose the learning rate since a number that is too little could lead to a lengthy training process that could become stuck, but a value that is too large could lead to learning a suboptimal set of weights too quickly or to an unstable training process. How quickly the model adapts to the situation is determined by the learning rate. Given the smaller changes to the weights made with each update, smaller learning rates necessitate more training epochs, whereas bigger learning rates produce quick changes and necessitate fewer training epochs.

The chest X-ray images were classified by the model as COVID-19 or NORMAL. Fig. 9 is an example of the image classification. The models can detect what category an image belongs to when given a randomly selected image as input.

The imaging similarities between normal and COVID-19 infection cases may have led to the misclassification, which is shown in Fig. 10.

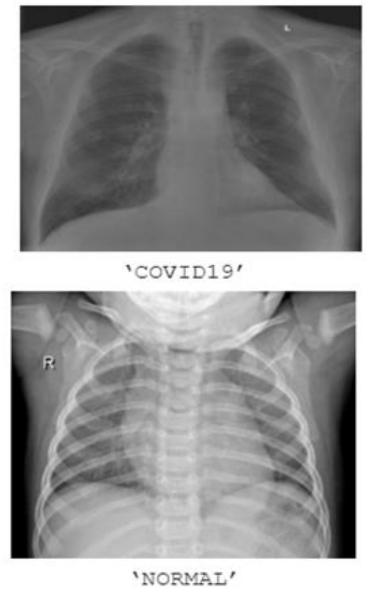

Fig. 9. Sample output of Covid-19 detection.

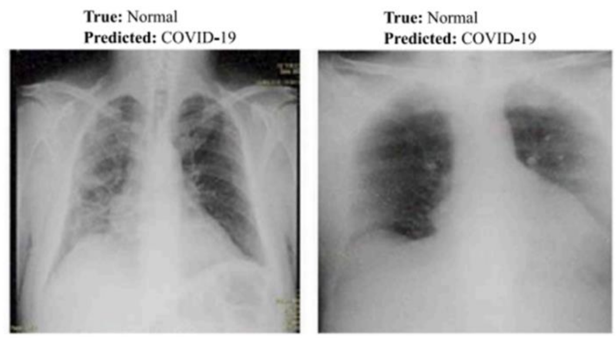

Fig. 10. Illustration of misclassification.

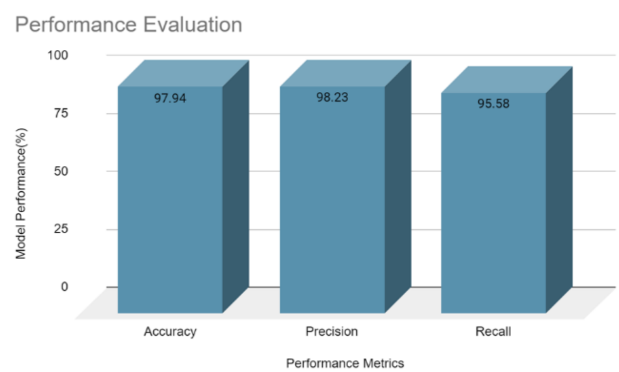

Fig. 11. Performance evaluation of proposed model.

The model's performance evaluation is graphically represented in Fig. 11. The x- axis and y- axis represent the performance metrics and model performance (%) respectively. The model obtained 97.94% accuracy, which outperforms other existing pre-trained models. The model also provides better precision and recall rate.

C. Discussions

The simulation results for the COVID-19 detection model using a modified VGG-16 architecture are promising, indicating a high overall accuracy of 97.94%. Precision, which measures the model's ability to correctly identify positive cases among the predicted positives, is notably high at 98.23%. The recall, representing the model's capability to identify all actual positive cases, is also strong at 95.58%. These metrics collectively suggest that the modified VGG-16 model exhibits a robust performance in distinguishing COVID-19 cases from normal cases.

In comparison with traditional detection methods, the high accuracy, precision, and recall values of the modified VGG-16 model underscore the potential of deep learning approaches in enhancing COVID-19 detection. Traditional methods often rely on manual interpretation or rule-based algorithms, which may lack the complexity and adaptability demonstrated by deep learning models. The precision and recall values above 95% indicate a low rate of false positives and false negatives, crucial for reliable COVID-19 diagnostics. The model's performance may be influenced by the diversity of the dataset, variations in image quality, and the representativeness of the COVID-19 cases. Moreover, the interpretability of deep learning models poses a challenge, making it crucial to ensure the clinical relevance and trustworthiness of the predictions.

In conclusion, the modified VGG-16 model exhibits a commendable performance in COVID-19 detection, outperforming traditional methods in terms of accuracy, precision, and recall. While these results are promising, further validation on diverse datasets and real-world clinical settings is necessary to establish the model's robustness and generalizability for practical implementation in the field of COVID-19 diagnostics. Additionally, efforts should be directed towards addressing interpretability concerns and ensuring seamless integration with existing healthcare practices.

V. Conclusion

According to the World Health Organization (WHO), more than five million people have been infected globally to date, and there have been about three lakh confirmed cases of death. Therefore, it is crucial to identify COVID-19 as soon as possible in order to stop its spread and lower its mortality. Currently, RT-PCR is the benchmark for diagnosing COVID-19. In this test, viral nucleic acid from sputum or a nasopharyngeal swab is found. This testing mechanism has a few drawbacks. The complicated and painful nature of this testing technique for the patients is another issue. As a result of these concerns, there is a huge need for alternative diagnostic techniques that deal with these issues. In this work a modified VGG-16 model was used for COVID-19 detection from chest X-ray images. This model classified the chest X-ray images into two categories: COVID-19 and NORMAL images. Finally, the performance of the proposed model is evaluated. The model has been validated on publicly available chest X-ray images. The best performance is obtained by the proposed model with an accuracy of 97.94%.

VI. Future Work

Therefore, in future work, the performance of the suggested methodology for multiclass classification issues will be established. In order to create a model that is more dependable, we also intend to investigate the application of optimization methods in conjunction with the DL models utilized in this study. In order to efficiently provide doctors with precise focal area detection during diagnosis and to facilitate early illness identification and prevention, the proposed model will be integrated with object detection.

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