COVIDnet: An Efficient Deep Learning Model for COVID-19 Diagnosis on Chest CT Images

Briskline Kiruba S
Department of Computer Science and Engineering
Manonmaniam Sundaranar University
Tirunelveli, Tamilnadu, India 627 012

Murugan D
Department of Computer Science and Engineering
Manonmaniam Sundaranar University
Tirunelveli, Tamilnadu, India 627 012

Petchiammal A
Department of Computer Science and Engineering
Manonmaniam Sundaranar University
Tirunelveli, Tamilnadu, India 627 012

***Abstract*—A novel coronavirus disease (COVID-19) has been a severe world threat to humans since December 2020. The virus mainly affects the human respiratory system, making breathing difficult. Early detection and Diagnosis are essential to controlling the disease. Radiological imaging, like Computed Tomography (CT) scans, produces clear, high-quality chest images and helps quickly diagnoses lung abnormalities. The recent advancements in Artificial intelligence enable accurate and fast detection of COVID-19 symptoms on chest CT images. This paper presents COVIDnet, an improved and efficient deep learning Model for COVID-19 diagnosis on chest CT images. We developed a chest CT dataset from 220 CT studies from Tamil Nadu, India, to evaluate the proposed model. The final dataset contains 5191 CT images (3820 COVID-infected and 1371 normal CT images). The proposed COVIDnet model aims to produce accurate diagnostics for classifying these two classes. Our experimental result shows that COVIDnet achieved a superior accuracy of 98.98% when compared with three contemporary deep learning models.**

Keywords*—*Coronavirus disease; reverse transcription polymerase chain reaction; computed tomography; deep learning

I. Introduction

The COVID-19 pandemic was the outcome of the Corona virus's rapid global spread. By 2022, there were 575 million COVID-19 patients, 6 million fatalities, and 12 billion vaccination doses [1]. The symptoms of COVID-19 include fever, chills, cough, headache, exhaustion, loss of smell, sore throat, runny nose, vomiting, and diarrhea. Affected individuals may also be asymptomatic. Affected individuals may also be asymptomatic. At least one-third of infected individuals don't have any symptoms at all. Identifying and reducing the spread of COVID-19 is a challenge task for medical experts. Therefore, there is an essential need to identify a faster and more accurate diagnostic methods for COVID-19.

Reverse Transcriptase and Polymerase Chain Reaction (RT-PCR) is a highly specific test that uses a sample taken from a human nose or throat. There have been reports of low COVID-19 sensitivity and it takes 3 to 4 days [2]. Patients with COVID-19 who undergo chest radiography (X-ray) [3] are defined as having bilateral air space consolidation due to inaccuracies in laboratory methods.

Chest radiography is crucial in the early detection and treatment of individuals with suspected or confirmed chest infections during the COVID-19 pandemic. It is entirely accessible in urgent care centers and emergency rooms. The combination of multi-focal peripheral lung abnormalities, such as GGO and/or consolidation, is described by X-ray [4]. These are frequently bilateral, and the COVID-19 diagnosis is challenging since other reasons of respiratory problems prevent consistent detection in X-rays.

Chest CT, a high-sensitivity alternative method for accurate COVID-19 diagnosis, is utilized in conjunction with X-ray imaging[5]. When COVID-19 is detected, the chest CT's main function is to diagnose the disease early [6]. Several advantageous COVID-19-related chest CT scenarios: There is no distinct test for COVID-19 and there is no additional expense to discover COVID; the chest CT examination is performed for other purposes such as cancer screening [7], operations [8], and neurological examinations [9]. People with poorer respiratory conditions underwent simply a chest CT and no other testing right away to figure out their COVID-19. Close contact with the infected patients results in probable COVID-19 [10], but the viral testing come out negative in this instance. To confirm COVID-19 confirms the abnormalities displayed inside the lungs, chest CT imaging is the sole treatment option.

Physicians and radiologists can assist COVID patients with a quick diagnosis by using an automatic diagnostic tool for COVID-19. For the detection of COVID-19 using chest CT, numerous investigations have been carried out. To create an automated technique for detecting COVID-19 [11], computer scientists have thoroughly researched the deep learning models. Despite these efforts, there is a growing need to make these models more reliable and realistically useful by improving their diagnostic performance. This work presents *COVIDnet*, an enhanced and effective deep learning model architecture. To increase COVID detection accuracy on chest CT images, the proposed COVIDnet is built on CNN architecture and has 22 layers. We created a dataset of 5191 CT images (3820 COVID-infected and 1371 normal CT images) from 220 CT scans from hospitals in Tamilnadu, India, in order to evaluate our model. When compared against three current deep learning models, including CNN, VGG16, and MobileNet, our COVIDnet model had the greatest accuracy of 98.98%.

The paper is organized as follows: Section II summarizes the related studies; Section III presents the proposed methodology. Section IV describes the experimental setup and results, and Section V concludes the paper.

II. Related Work

The COVID-19 pandemic has turned into a significant worldwide problem as researchers try to find a way to stop the virus' spread and infection rate. Several research projects have started based on the Al systems recommended for COVID-19 detection CT images. Studies have shown the efficiency of CT scan image processing for diagnosing COVID-19 while also demonstrating the degree of infection, which can be significant for improved treatment options. Several researchers have presented AI-based COVID-19 identification methods. For the most part, deep learning-based approaches have generated very encouraging detection accuracy for COVID-19. We have reviewed a few studies and compared them to our proposed model.

Several studies are cited when discussing chest CT imaging. 746 chest CT scan pictures are analyzed using the LeNet-5 CNN model [12], which forecasts COVID and normal. Here, the dataset has been upgraded and increased utilizing augmentation techniques, making it more useful and accurate to 86.06%. The 746 chest CT scans were trained using 147 million parameters and three distinct learning techniques using the EfficientNet model [13], which achieved an accuracy of 89.7%. For COVID-19 feature extraction and binary classification, an optimized DL network Whale Optimization Algorithm (WOANet) [14] was used. They employed CCT pictures to diagnose COVID-19 using the ResNet-50 CNN network. They optimized the hyperparameters to achieve the best performance using the backpropagation and WOA algorithms. Preprocessing and Region of Interest (ROI) extraction are not required for the suggested technique. They applied COVID-CT dataset.

A deep learning-based system for the automated diagnosis of COVID-19 patients was built via GAN architecture [15]. The suggested framework offered a strong performance at many phases and an efficient feature extraction. To produce additional Chest Computed Tomography (CCT) images for DL network training, the initial step is augmenting the data using a generative adversarial network (GAN) architecture. In the second stage, the Generative Adversarial Network (GAN) hyperparameters are optimized using the WOA optimization. The major goal was to prevent overfitting and instability problems. Finally, COVID-19 patients were automatically classified during the classification step using a pretrained InceptionV3 DL model. They made use of the 2,482 CCT scan images from the SARS-CoV-2 CT-Scan dataset. The experimental investigation demonstrated that the suggested model performed better than other cutting-edge models.

A deep learning-based automated screening strategy was developed by the local attention classification model [16] to separate CT samples found to have COVID-19 or influenza-A viral pneumonia from the sample of patients with healthy lungs. The experimental result showed an overall classification accuracy of 86.7% for the 618 lung CT images dataset. In order to extract the best attributes for identifying COVID-19 and differentiating it from healthy cases and pneumonia infections, a completely automated system was presented using CNN [17]. The 400 CT scans in the used dataset resulted in an overall COVID-19 case detection accuracy of 96%.

A better version of DRENet [18] is an autonomous deep-learning identification method to help medical professionals find and identify COVID-19-infected individuals. The obtained dataset included CT scans from 100 bacterial pneumonia samples, 88 COVID-19 samples, and 86 healthy samples. With an accuracy of 95%, this DRENet deep learning network could identify and categorize samples that were contaminated with COVID-19 and bacterial pneumonia. A system to provide a clinical identification of the pathogenic examination utilizing a CNN-based [19] automated technique in detecting distinctive COVID-19 characteristics. With 217 cases in the dataset, the accuracy was 82.9%.

TABLE I. TN-COVID Dataset

S.No.	Category	No. of chest CT studies	No. of images
1	COVID	166	3820
2	Normal	54	1371
	Total	220	5191

Using a dataset with 1495 patients with COVID-19 and 1027 patients with CAP, an adaptive feature selection guided deep forest (AFSDF) algorithm [20] was used to classify COVID-19 from chest CT images. This model was developed using a high-level feature representation. A feature selection method was applied to lessen the redundancy of the features based on the trained deep forest model. The COVID-19 classification model was adaptively updated to include this feature selection technique. There were 91.79%, 93.05%, 89.95%, and 96.35% values for accuracy, sensitivity, specificity, and area under the ROC curve, respectively.

Developing an automated approach for classifying lung CT scans is still challenging due to the complexity of diagnosing inflammatory and infectious lung illness via visual assessment. An appropriate norm as a visual examination is subject to errors due to the vast number of patients requiring diagnosis. A method that uses a CNN-based [21] automated technique to identify specific COVID-19 traits to provide a clinical identification of the pathogenic evaluation. With 217 examples in the sample, the accuracy was 82.9%.

The aforementioned deep learning models for COVID-19 detection use chest CT images to address the working models. We performed tests on the independently gathered raw TN-COVID dataset and contrasted its performance with that of the publicly integrated dataset using accepted assessment metrics. The effectiveness of the current deep learning models to be further enhanced in order to create new models for future development and to offer visualizations for better model explanation.

III. Materials and Methodology

Fig. 1 shows the proposed methodology for COVID-19 detection using deep learning and chest CT images. Chest computed tomography (CT) images from different hospitals in Tamilnadu were gathered to create the dataset. The chest CT images are cleaned, annotated, and expanded using image augmentation techniques. Then, the final chest CT dataset is split into training, testing, and validation sets to evaluate the efficacy of the proposed COVIDnet model using five performance metrics. The final model is implemented into a

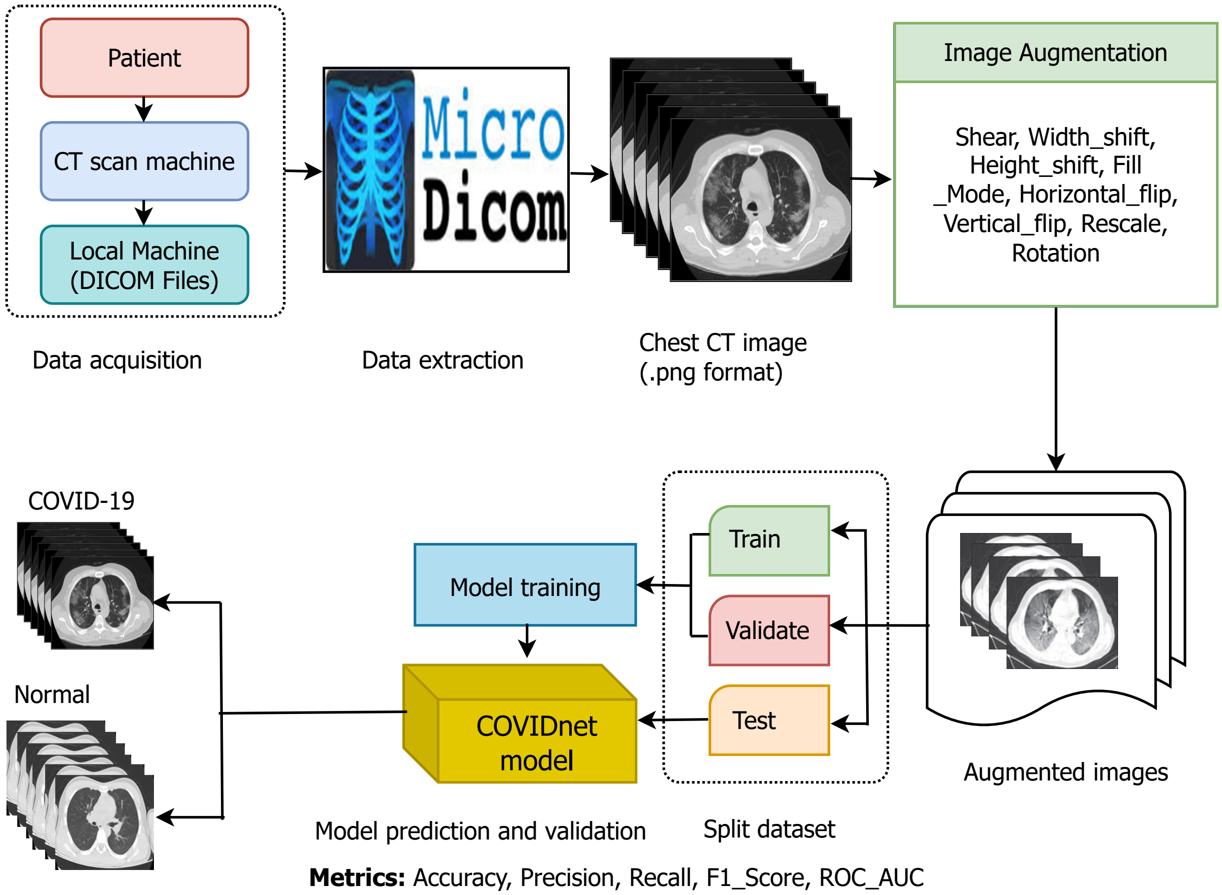

Fig. 1. The Proposed COVID-19 Detection Methodology using COVIDnet Model.

web-based application to identify whether the given chest CT image is from COVID-19 or a normal patient.

A. Data Collection

The chest CT dataset used in this study is directly collected from a hospital in Tamilnadu, India. The CT scanner (Aquilion Lightning Model Tsx 035a), which scans the chest and records the information on a local device, is used to acquire the data. The *MicroDicom viewer* application is used to extract the chest CT images from the DICOM (Digital Imaging and Communications in Medicine) format files that the CT scan machine stores internally. The extracted 16-bit grayscale images in `.PNG` format have a resolution of 512 by 512 pixels. With the assistance of radiologists and medical professionals, the extracted chest CT images are cleaned. After cleaning, there were 1371 and 3820 images belonging to 54 healthy and 166 COVID-infected patients, respectively. The final dataset, named the *TN-COVID dataset*, consists of 5191 images from 220 CT studies. Additional metadata and anonymized patient information, including patient history and RT-PCR report, are collected. Table I displays an overview of the dataset.

B. Image Augmentation

Data Augmentation techniques are usually employed to increase the size of a training set in order to improve the performance while reducing the overfitting of deep learning models. A number of of common image transformation operations are used to generate more training samples. They are, random rotation and zoom, height and width shift, horizontal and vertical flip, and shear. These operations generate multiple images from each image and help increases the generalization of the trained models.

C. COVIDnet Architecture

For accurate COVID diagnosis in chest CT scans, the proposed COVIDnet model is built with 22-layers. Convolutional layer, pooling layer, flattening layer, dense layer, and activation function are the five key components of the proposed model. Fig. 2 shows the COVIDnet model architecture employing these layers. Below is a description of each of these layers.

Convolutional Layer The convolution operation is applied to the input in the convolution neural network and the output is passed to the following layer. Convolution reduces the size

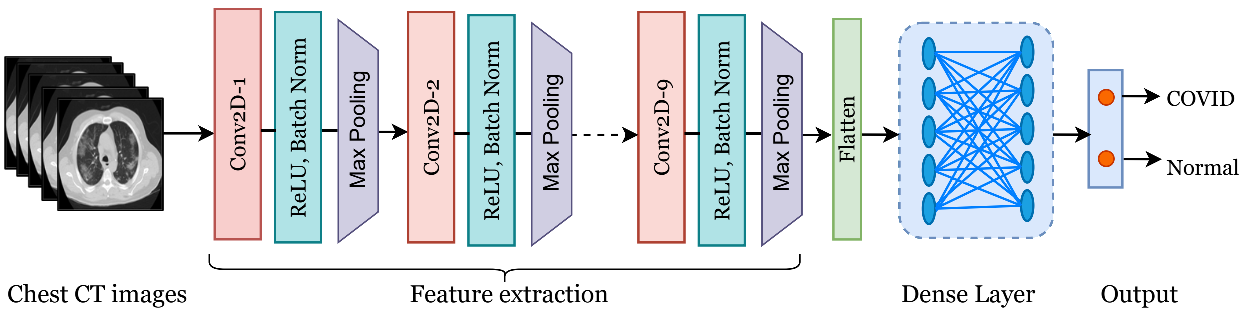

Fig. 2. The Proposed COVIDnet Architecture with 22-Layers for COVID-19 Detection on Chest CT Images.

of the image by combining all of its pixels into a single value. The parameters F, m, B, and W_j can be used to conduct convolution operations. F gives the kernel filter size, m sets feature mappings, B stands for bias, and W_j assigns the kernel weight. By employing a dot product to create one or more matrices, it extracts the feature from the input photos. To remove the features from left to right, convolutional filters are employed. Equation (1) denotes the output of the convolutional layer operation.

Pooling Layer A pooling layer is included when the image size is too huge, to shrink the feature map's size. It helps in speeding up computation, lowering the number of training parameters, and avoid overfitting. The pooling layer is usually added after convolutional layer. There are two categories of pooling: average pooling and maximum pooling. The average value for each component on the feature map is computed using average pooling, while the highest value for each component is generated using maximum pooling. The two hyper-parameters for the pooling layer are Filter and Stride. Equations (2) and (3) denotes the pooling operations. The step that kernels take to shift on the input image is marked by S, while the kernel size is denoted by F.

Flatten Layer It reduces the feature map matrix in its entirety to a single column. The fully linked layer received this input from the single column matrix to categorize the chest CT image.

Dense Layer The dense layer's function is to categorize the output from the convolutional layer for classification. Which features match mostly in a given class are determined by the preceding layer output. It outlines the high-level feature's weights. The input is the weighted average, which is then processed by a nonlinear function acting as an activation function. To calculate the weights and the previous layer, the fully linked layer supplies the accurate probabilities from various classes. The output is classified using the activation function.

Activation Function The activation function defines the sum of the weighted inputs transformed into outputs in the network. Three common activation functions are ReLU, Sigmoid, and Leaky ReLU. The performance of MaxPooling2D is proved by these three activation functions, as shown in equations (4) and (5).

It shows that x is a real number. A sigmoid function has a 0 to 1 range and resembles an S-shaped curve. To change an

TABLE II. LIST OF SYMBOLS

Parameter	Description
F	Specifies the kernel (filter) size
B	Bias
W_j	Weight of the kernel
S	Stride size
$f(z)$	Softmax function
Y_i^1	Output of a convolutional layer, where i indicates the i^th feautre map
W_1, H_1	Width and Height of input
$l-1$	Fully connected layers
$m_1(l-1)$	Feautre maps

actual value into one that is easier to understand and can be translated into a probability score. Because sigmoid function networks take longer to train than other types of networks, the vanishing gradient problem quickly converges to 0. ReLU is a linear function that resolves the vanishing gradient issue by setting zero on all negative inputs. Based on the ReLU activation function, a "leaky ReLU" model leaks some positive values to 0 while defining the small slopes with negative values. The slope of the small negative function is represented by the value of x, which is less than zero.

Fig. 2 shows the proposed 22-layer CNN model. Moreover, Table III shows the list of steps used in the development and validation of the proposed COVIDnet model. Nine convolutional, max-pooling, and leaky ReLU layers make up the proposed COVIDnet model. Batch normalization speeds up and improves the stability of the model processing by normalizing, re-centering, and scaling the input. The neural network can be trained more quickly and effectively using the Adam optimizer by adjusting the parameters, first and second gradient moments to modify the learning rate and lower the loss. To discover the optimum accuracy for our suggested model, the deep learning model construction process combines all the layers, activation functions, and optimizer values. We changed the activation function and optimizer settings for every parameter in the extra layers of the proposed model. Our basic layer model is enhanced with 2D Convolutional and MaxPooling layers to produce improved results for two class

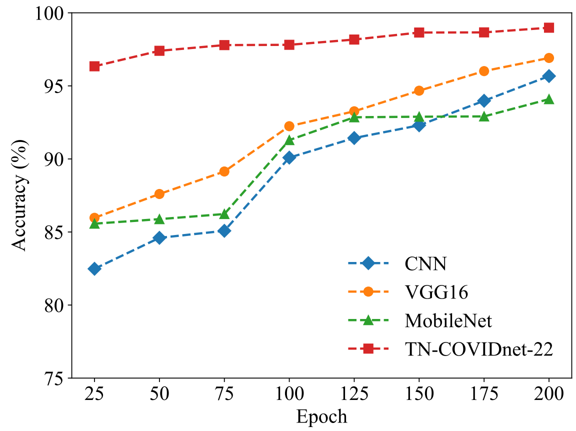

Fig. 3. Comparison of Classification Accuracy of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet). The Proposed COVIDnet Model Obtained the Highest Classification Accuracy of 98.98% with Epoch 200.

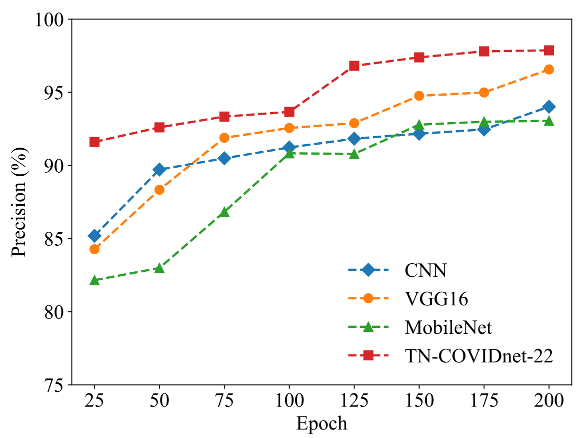

Fig. 4. Comparison of Precision Score of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet). The Proposed COVIDnet Model Obtained the Highest Precision Score of 97.87% with Epoch 200.

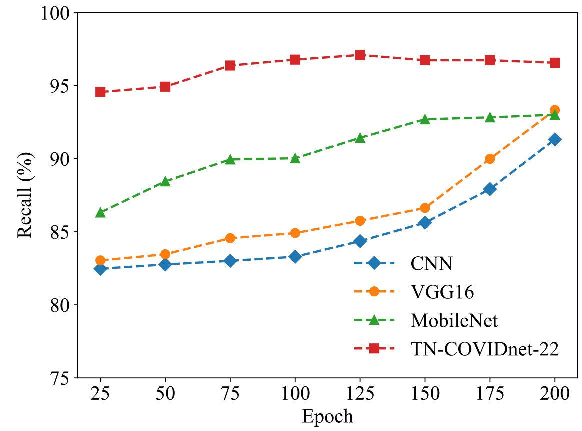

Fig. 5. Comparison of Recall Score of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet). The Proposed COVIDnet Model Obtained the Highest Recall Score of 96.57% with Epoch 200.

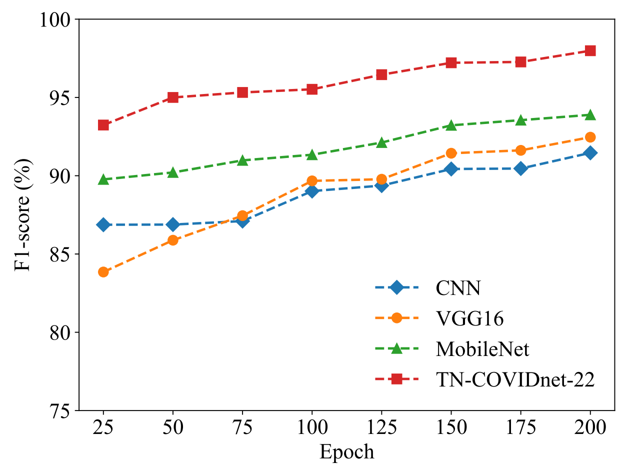

Fig. 6. Comparison of F1-Score of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet). The Proposed COVIDnet Model Obtained the Highest F1-Score of 97.99% with Epoch 200.

classifications.

IV. Experimental Results and Discussion

A. Experimental Setup

Python 3 was used to implement the proposed COVIDnet model utilizing the Keras and TensorFlow frameworks. To increase the training pace, we ran all of our tests on the GPU-powered Kaggle platform. Adam optimizer is used to train the proposed 22-layer COVIDnet model. The batch size is 32, and the learning rate is 0.0001. Different models were trained using various epochs (25, 50, 75, 100, 125, 150, 175, and 200), and we compared the model performance to prevent over-fitting and increase the model's generalizability. The model evaluation is generalized using a 5-fold cross-validation method. Additionally, accuracy, precision, recall, F1-Score, and ROC-AUC, five common performance metrics, were utilized to compare the performance of the proposed COVIDnet with three conventional deep learning models: simple CNN, VGG16, and MobileNet. Based on ImageNet, the weights of the VGG16 and MobileNet models were initialized.

B. Results

Table IV to Table VIII and Fig. 3 to Fig. 7 compare the experimental findings. As shown in Table IV and Fig. 3, the COVIDnet model obtained the highest classification accuracy of 98.98% with epoch 200. The VGG16 model comes in second with a 96.91% accuracy rate. The accuracy rate for the MobileNet is the lowest (94.10%) as shown in Table IV and Fig. 3. As shown in Table V and Fig. 4, the COVIDnet model also obtained the highest precision of 97.87% with epoch 200. The VGG16 model comes in second with a precision score of

TABLE III. COVIDNET MODEL DEVELOPMENT AND VALIDATION

Input:	TN-COVID chest CT image dataset (5191 images)
Output:	**COVIDnet** model and prediction results (accuracy, precision, recall, F1-Score, and ROC-AUC)
Step 1:	Import sklearn, tensorflow, keras, and other libraries
Step 2:	Load the TN-COVID dataset
Step 3:	Perform image augmentation using ImageDataGenerator() by Rotation, shear, width_shift, height_shift, channel_shift, fill_mode, horizontal_flip, vertical_flip, and rescale.
Step 4:	Split the augmented images into train(60%), validation (20%) and test (20%) sets and load them into different variables.
Step 5:	Initialize *COVIDnet* model and add nine Conv2d layers and nine Maxpool2d layers. The convolution operation is performed by the below equation: $$Y_i^1 = B_i^1 + \sum_{j=1}^{m_1(I-1)} F_i, j * W_j^{(l-1)} \quad (1)$$ Pooling operations are performed by adjusting the width and height of feature maps which is performed by the below equations: $$W_2 = \frac{W_1 + F}{S} + 1 \quad (2)$$ $$H_2 = \frac{H_1 + F}{S} + 1 \quad (3)$$
Step 6:	Add batch normalization and activation (ReLU) function to the model. The ReLU function is shown below. $$f(z) = \max(0, x) \quad (4)$$ $$f^{'}(z) = \begin{cases} 1 & \text{if z} > 0 \\ 0 & \text{if z} \leq 0 \end{cases} \quad (5)$$
Step 7:	Add a dense layer using dense() with an activation function of Softmax $$f(z)_i = \frac{e^{z_j}}{\sum_{k=1}^{k} e^{z_k}} forj - 1, ..., k \quad (6)$$
Step 8:	Train the *COVIDnet* on the training dataset using fit_generator(). The validation set is used to evaluate the model performance during training.
Step 9:	Test the accuracy of the trained *COVIDnet* model on the test set and report the final results using five performance measures.

96.56%. The model from MobileNet has the lowest precision at 93.05%. Aditionally, the COVIDnet model obtained the highest recall rate of 96.57% with epoch 200, as shown in Table VI and Fig. 5. The VGG16 model, which has a recall rate of 93.33%, comes next. The CNN model's 91.32% recall rate is the lowest.

Additionally, as shown in Table VII and Fig. 6, the COVIDnet model had the highest F1-score of 97.99% with epoch 200. With an F1-score of 93.89%, the MobileNet model comes in second. With an F1 score of 91.46%, CNN and VGG16

TABLE IV. Comparison of Accuracy of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet).

S.No.	Epoch	Models			
		CNN	VGG16	MobileNet	COVIDnet
1	25	82.48	85.97	85.57	96.34
2	50	84.60	87.60	85.88	97.40
3	75	85.08	89.14	86.23	97.79
4	100	90.09	92.24	91.29	97.81
5	125	91.43	93.26	92.85	98.17
6	150	92.3	94.67	92.89	98.65
7	175	93.98	96.01	92.91	98.66
8	200	95.67	96.91	94.10	98.98

TABLE V. Comparison of Precision Score of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet)

S.No.	Epoch	Models			
		CNN	VGG16	MobileNet	COVIDnet
1	25	85.19	84.27	82.16	91.61
2	50	89.72	88.34	82.99	92.60
3	75	90.49	91.89	86.83	93.34
4	100	91.23	92.56	90.83	93.66
5	125	91.83	92.89	90.79	96.81
6	150	92.17	94.76	92.79	97.39
7	175	92.46	94.99	92.99	97.80
8	200	94.02	96.56	93.05	97.87

TABLE VI. Comparison of Recall Score of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet)

S.No.	Epoch	Models			
		CNN	VGG16	MobileNet	COVIDnet
1	25	82.47	83.04	86.32	94.57
2	50	82.76	83.46	88.45	94.93
3	75	83.01	84.56	89.95	96.38
4	100	83.29	84.91	90.03	96.78
5	125	84.36	85.75	91.43	97.10
6	150	85.62	86.63	92.70	96.74
7	175	87.92	89.99	92.83	96.74
8	200	91.32	93.33	93.01	96.57

models are tied for last. As shown in Table VIII and Fig. 7, the COVIDnet model also obtained the highest ROC-AUC score of 98.11% with epoch 200. With a ROC-AUC score of 94.66%, the MobileNet model comes in second. The CNN model's ROC-AUC score of 90.00% is the lowest. Table IX and in Fig. 8 compare each of the five performance measures for four models with 200. It should be highlighted that the proposed COVIDnet model outperformed all other models on the TN-COVID dataset in every statistic. These enhanced outcomes show that the COVIDnet model may aid automated diagnosis of COVID in hospitals.

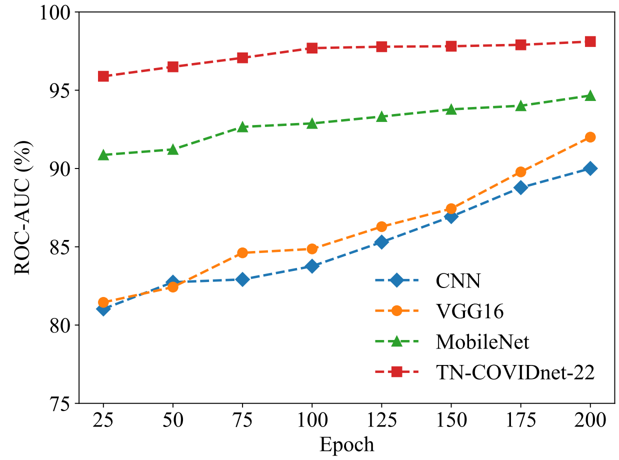

Fig. 7. Comparison of ROC-AUC Score of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet). The Proposed COVIDnet Model Obtained the Highest ROC-AUC of 98.11% with Epoch 200.

TABLE VII. Comparison of F1-Score of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet)

S.No.	Epoch	Models			
		CNN	VGG16	MobileNet	COVIDnet
1	25	86.87	83.85	89.77	93.24
2	50	86.88	85.88	90.21	95.00
3	75	87.10	87.45	90.98	95.32
4	100	89.02	89.67	91.34	95.52
5	125	89.37	89.78	92.12	96.46
6	150	90.43	91.44	93.22	97.21
7	175	90.46	91.62	93.55	97.27
8	200	91.46	92.46	93.89	97.99

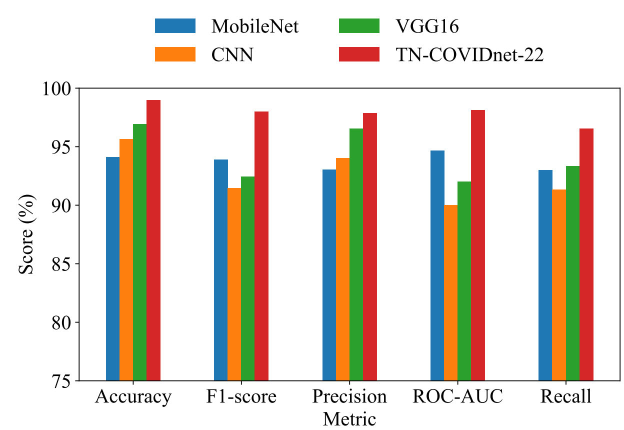

Fig. 8. Comparison of Accuracy, Precision, Recall, F1-Score, and ROC-AUC Scores of Four Models with Epoch 200.

V. Conclusion

The human society is severely impacted by COVID-19. Several automated methods for precise and speedy COVID-19 diagnosis based on Chest CT images have been proposed in recent years with the advent of AI techniques. In order

TABLE VIII. Comparison of ROC-AUC Score of COVIDnet with Three State-of-the-Art Models (CNN, VGG16, and MobileNet)

S.No.	Epoch	Models			
		CNN	VGG16	MobileNet	COVIDnet
1	25	81.03	81.45	90.87	95.89
2	50	82.74	82.43	91.22	96.50
3	75	82.91	84.61	92.66	97.07
4	100	83.76	84.86	92.88	97.69
5	125	85.30	86.29	93.32	97.78
6	150	86.93	87.44	93.78	97.81
7	175	88.78	89.78	94.01	97.90
8	200	90.00	92.00	94.66	98.11

TABLE IX. Comparison of Accuracy, Precision, Recall, F1-Score, and ROC-AUC Scores of Four Models with Epoch 200

Metric	Models			
	CNN	VGG16	MobileNet	COVIDnet
Accuracy	95.67	96.91	94.09	98.98
Precision	94.02	96.56	93.05	97.87
Recall	91.32	93.33	93.01	96.57
F1-score	91.46	92.46	93.89	97.99
ROC-AUC	90.00	92.00	94.66	98.11

to identify COVID-19 using chest CT images, this research introduces a new deep learning-based model called COVIDnet. For precise COVID-19 detection on chest CT scans, a 22-layer binary classifier (normal or COVID) is proposed. On the TN-COVID dataset, the proposed COVIDnet outperformed three current deep learning models (basic CNN, VGG16, and MobileNet) with an accuracy of 98.98%, precision of 97.97%, recall score of 96.57%, F1-score of 97.99%, and ROC-AUC of 98.11%. These excellent outcomes demonstrate the path in which the COVIDnet model is being implemented into COVID-19 diagnostic tools in hospitals.

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