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Research Article

Deep Learning Model for COVID-19 Diagnosis: Improving Accuracy and Sensitivity in Early Detection

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ABSTRACT
The continuous COVID-19 pandemic, caused by the SARS-CoV-2 virus, required fast and efficient diagnostic tools. This work presents a deep learning-based system, using convolutional neural networks, for the detection and diagnosis of COVID-19 through computed tomography tests, aiming to assist specialized medical professionals. A total of 746 Computed Tomography images (CT), were used in this work, one of the largest publicly available chest computed tomography dataset for research into COVID-19. Our proposed technique showed the accuracy of more than 99% for the training set, with high sensitivity and specificity, and achieved 97% on the validation set. Such results would hint at the very possible implementation of our deep CNN approach in clinical diagnostic settings, particularly for COVID-19 testing, to enhance early detection and management for patients.

Keywords:* *COVID-19, Deep Learning, Medical AI, Viral Detection, CT Diagnosis.

1. Introduction

The beginning of the health crisis that would reshape the world took place in December 2019 with the detection of a novel coronavirus in Wuhan, China. This virus, subsequently named SARS-CoV-2, causes a new illness called COVID-19 and has since caused millions of infections and deaths worldwide. The pandemic was still quite a large challenge to health systems, economies, and societies throughout the world per September 2024.
Symptoms of COVID-19 range from mild complaints of the respiratory system to life-threatening ARDS [1, 2]. Due to this rapid person-to-person mode of transmission, there was an immediate need to develop rapid, accurate, and reliable diagnostic tools for COVID-19 to manage the spread of the virus effectively and provide timely treatment to the affected individuals [3]. This is where medical imaging became an important modality in the diagnosis and management of COVID-19. None other than CT and X-rays have proven to be two of the most highly sensitive diagnostic modalities able to depict typical lung changes that are quite characteristic of COVID-19 infection [4]. Their interpretation requires specialized expertise and is also time-consuming, especially in regions seeing a surge of cases. Figure 1 illustrates various medical imaging techniques commonly used in healthcare, including CT and X-rays, which have proven crucial in COVID-19 diagnosis ease of use.

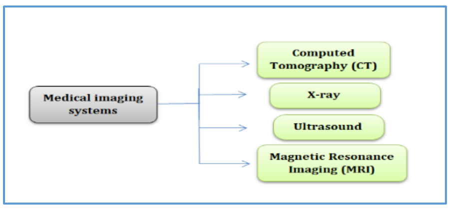

Fig 1. *Medical imaging system.1*

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These challenges have lately been the inducement for major research interest in the adoption of artificial intelligence techniques, particularly those related to deep learning, for the assistance of rapid and accurate analyses of medical images referring to COVID-19 diagnosis. Deep learning algorithms, especially CNNs, have achieved remarkable successes in a variety of medical imaging tasks, including the detection of pulmonary diseases [5, 6]. The transmission of this novel virus from one person to another has been verified[7].

This research work employed the usage of CT pictures that was done with the help of Artificial Intelligence, including machine learning and deep learning. to accurately detect and diagnose COVID-19 best procedures for early detection and illness diagnosis that are considered to be the most effective. However, Deep Learning has lately become one of the crucial Artificial Intelligence AI technologies for getting precise diagnoses in health imaging and the automated identification of pulmonary diseases [8, 9]. The deep learning model has the potential to revolutionize the area of bioinformatics due to its exceptional performance, ability to recognize common objects, and handle complex and diverse data.

Deep learning algorithms have been employed to actively analyze and recognize pictures related to the COVID-19 epidemic. Several scientists have conducted research using several deep learning systems to categorize and predict COVID-19 infections, including the use of many advanced techniques. Some of the sophisticated forms of machine learning developed by modern AI technology are GAN, CNN, Residual, LSTM, and Auto Encoder. [10]

Machine Learning ML is the subfield of Artificial Intelligence that employs a set of algorithms for automated data analysis, pattern recognition, without a prespecified pattern, which is information about the patterns of communication. [11] Clinical diagnosis frequently involves the use of methods based on machine learning, and these techniques could be useful in other points of health care such as the identification of diseases and illnesses, medical image analysis, prediction of events like an epidemic, and others. [10] Presumably; Machine learning algorithms are applied in the medical image processing and diagnosis, the prediction of epidemic situation [12].

Some recent research articles in the context of the current pandemic utilized several techniques. Some of the Machine Learning techniques that have been used in this study include K-means, Support Vector Machines SVM, Random Forest, Linear Regression, other Machine Learning algorithms. This paper applies Algorithms for the purpose of prediction and detection of SARS-CoV2 [10]. This research aims to investigate the fast identification and recognition of Covid-19 utilizing Artificial Intelligence AI technology, and approaches for enhancing deep learning. Figure 2 depicts the whole procedure of the COVID-19 diagnostic system.

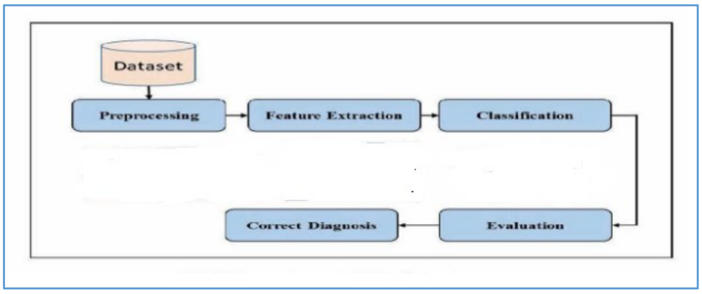

Fig.2 The general steps of the COVID-19 diagnosis system

Certain benefits of deep learning applications for COVID-19 diagnosis may include the following:

- Rapid screening: AI algorithms can interpret images in a few seconds, which might reduce diagnostic time.
- Consistency: AI will give consistent interpretations with minimum human error or fatigue.
- Resource optimization: AI can rapidly triage potential COVID-19 cases to optimize medical resources.
- Remote diagnosis: AI systems may allow for telemedicine solutions that reduce virus transmission risks in healthcare settings.

Though many works reported the use of deep learning for COVID-19 diagnosis, there is still dire need for models that assure high accuracy and reliability across diverse patient populations and dissimilar conditions of imaging. Besides, most of the previous studies have been conducted on relatively smaller dataset sizes, which may have an influence on the results generated particularly in terms of generalization to larger datasets.

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This paper presents a new concept in deep learning based on CNNs for the identification and diagnosis of COVID-19 from CT scans. The work will cover the deficiencies in previous studies by using one of the largest publicly available chest CT scan datasets, containing 746 images collected from both COVID-19 positive and negative cases. We also believe that our model would show high accuracy, sensitivity, and specificity in distinguishing COVID-19 cases from non-COVID cases once it is trained on this vast dataset.

The rest of the paper is organized as follows: Section 2 reviews the related work in AI-based COVID diagnosis. Section 3 describes our proposed methodology related to data preprocessing, model architecture, and the training process in detail. Section 4 presents our results and discusses implications. Finally, Section 5 concludes the paper and provides directions for future research. This work will be another contribution to ongoing efforts against the COVID-19 pandemic, offering a robust, AI-powered tool that might contribute to the rapid and accurate diagnosis by healthcare professionals, potentially improving outcomes and helping in the control of virus circulation.

2. Related work

Since the debut of COVID-19, several deep-learning research using CT scan pictures and X-ray chests for COVID-19 detection have occurred and been published in the literature. Wu et al. [13] proposed a coronavirus screening approach using deep learning and multi-view fusion. The framework utilizes ResNet50, a form of Convolutional Neural Network CNN. Jin et al. [14] developed a coronavirus detection method using an artificial intelligence technique called ResNet152, which is a variant of CNN.

Yousefzadeh et al. [15] developed the deep learning model ai-corona, which specifically targets CT images. The architecture incorporates many CNN variations, such as Xception, EfficientNetB0, DenseNet, and ResNet. Chen et al. [16] used a deep learning approach to identify COVID-19 in CT scans. They employed a robust pre-trained system named UNet++ for this purpose. Initially, UNet++ accurately delineated the specific region of interest from CT scans.

In order to identify cases of COVID-19, Elghamrawy and Hassanien [17] devised a method for diagnosing and predicting the condition of patients infected with the coronavirus. They used the Whale Optimization Algorithm WOA in conjunction with Convolutional Neural Networks CNN utilizing CT samples. WOA has been used for prognosis, whereas CNN has been utilized for diagnosis in this approach.

Narin et al. [18] propose three deep learning methods, namely Inception-ResNetV2, InceptionV3, and ResNet50, for the automated prediction of new COVID-19 cases using X-ray images of the coronavirus. Rahimzadeh and Attar [19] proposed an enhanced Convolutional Neural Network CNN to identify specific instances of coronavirus by analyzing X-ray data. The system was enhanced by combining two CNN architectures, ResNet50V2 and Exception, to use their multiple extraction capabilities.

Jabaar, M. A., and Alsaad, S. N. [26] propose a technique for detecting altered photographs by using a Deep Learning system that utilizes a Convolutional Neural Network CNN to identify pictures that have been digitally combined. The results demonstrate a training accuracy of 99.19% and a testing accuracy of 87.438%.

3. Proposed Methodology

Figure 3 illustrates the system's architectural design at an elevated level of abstraction. The content is categorized into two primary sections: CNN model construction and preprocessing.

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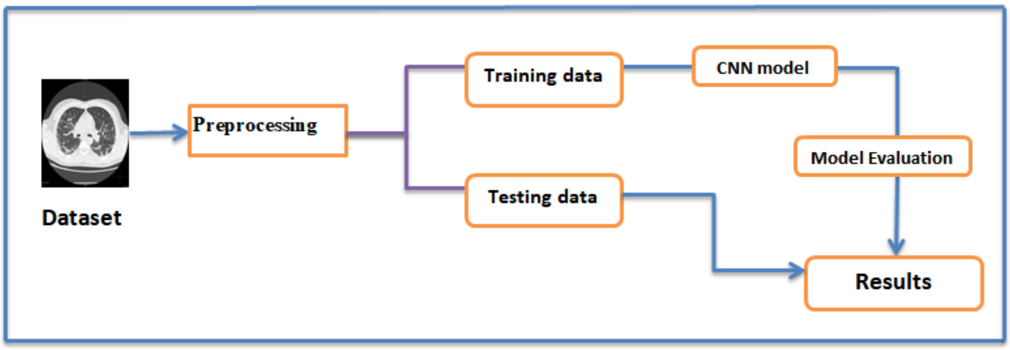

Fig 3. The proposed system

3.1 Preprocessing

All images, COVID-19 or not, are preprocessed by being converted to RGB format. The data set must be normalized by shifting to a certain range, the range is from (0,225) to (0 and 1). The normalization process is often used by default, assuming that pixel values consistently fall within the range of 0 to 1. This makes the operation straightforward and efficient. To expedite the convergence of CNN and attain the global minimum of loss values linked to the validation data, it is necessary to reduce the size of the picture to (192x192) pixels. The resizing stage will aid in speeding up the processing process and improving processing methods, and then image enhancement..

Algorithm 3.1 **Image Enhancement**.

Algorithm (3.1): Image Enhancement
Input: **CT image**
Output: Normalize CT images
Begin **- Step 1: Reading (CT) image.** **- Step 2: Converting the image to the RGB format.** **- Step 3: Resizing the CT image to the range (192x192) pixels.** **- Step 4: Image Enhancement.** **- Step 5: Normalizing the CT image (0,255) values to the range (0,1).** **- Step 6: Generating image normalization.** **End**

Algorithm (3.2) illustrates Image Enhancement of the CT image

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Algorithm (3.2) Normalizing the CT image

Input CT image
Output Normalizing the CT image

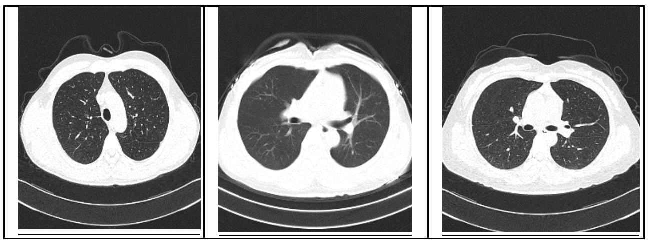
Begin
- **Step 1: Normalizing the pixel values from the range (0-255) to the range (0-1) by dividing each pixel value/ (225.0)**
- **Step 2: Normalizing = pixel values / 255.0**
- **Step 3 Minimum pixel value = 0.0**
- **Step 4: Normalizing: 0.0 / 255.0 = 0**
- **Step 5: Maximum pixel value = 255**
- **Step 6: Normalizing: 255.0 /255.0 =1**
- **Step 7: GeneratingCT image normalization**

End

3-2 Dataset

This study uses a supervised classification algorithm to divide a collection of images into two categories: COVID-19 and non-COVID. This study used a dataset based on CT scan images to predict pneumonia in COVID-19 patients [20]. The COVID CT Dataset comprises 746 images, 349 of which are COVID-19 images acquired from 216 COVID-19 patients and 397 of which are non-COVID images. Figure 4 depicts CT scans. The dataset was partitioned into training and testing sets using binary classification on CT scan pictures to discern whether the patient was diagnosed with COVID-19 or not. The COVID-19 pictures were acquired from bioRxiv. bioRxiv (https://www.biorxiv.org) and medRxiv from (https://www.medrxiv.org). The data are available at https://github.com/UCSD-AI4H/COVID-CT.

(a)



(b)

Fig 4. (a) *CT scan images of a lung infected with COVID-19.* ***(b)*** *CT scan images of a normal lung*

3-3 CNN Structure

This section discusses the proposed Convolutional Neural Networks CNN based on chest CT images to classify and aid clinicians in the detection of COVID-19. The model does well with COVID-19 case categorization. The proposed model is divided into two parts: training and classification. A training portion was generated using a convolutional neural network. Its purpose is to train a tagged Dataset including chest CT scans of individuals

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infected with COVID-19 and chest CT scans of those without COVID-19. The second component attempts to assess whether a CT image input corresponds to an infected person.

The CNN model is trained using a dataset of 746 photos, consisting of 397 non-COVID images and 349 COVID-19 images. 80% of the photos in the dataset were allocated to the training set, while the remaining 20% were assigned to the test set. We have conducted training on a Convolutional Neural Network CNN, the input size was 192×192×3. Each image in the dataset was preprocessed by the deep neural network's specifications. The two important steps involved were: Converting images to RGB, resizing, and normalization. In the deep CNN model, ten layers of Convolutional, Pooling, and Fully Connected layers are used.

A kernel (or filters) of various sizes and numbers will be used to complete the procedure, as well as other activities including stride and padding. All input nodes are flattened as a one-dimensional array in the Fully Connected layer. There are two activation functions Softmax and RELU are used. After the convolutional layer, RELU is applied, and the Softmax function is used to classify the Conducting picture classification into COVID and non-COVID groups. The training method employs the standard ADAM optimizer with a batch size of 100. The maximum number of epochs is set to 30, and the Loss function is determined using categorical cross-entropy. The random technique is used to test the model's effectiveness. Dropout is used to avoid overfitting while training the model. In the Decision Layer, these neurons were utilized to predict classes.

The deep neural network's preprocessing instructions were applied to each image in the dataset. The three key processes were converting photos to RGB, resizing, and normalizing. The sequential CNN model used in our research is shown in the method stages below. The Convolution operation extracts several visual characteristics, including color identification, edge detection, and corner finding. A kernel (or filters) of various sizes and numbers will be used to complete the procedure, as well as other activities including stride and padding. All input nodes are flattened as a one-dimensional array in the Fully Connected layer. There are two activation functions Softmax and RELU are used.

After the convolutional layer, RELU is applied, and the Softmax function is used to classify the Conducting picture classification into COVID and non-COVID groups. The training method employs the standard ADAM optimizer with a batch size of 100. The maximum number of epochs is set to 30, and the Loss function is determined using categorical cross-entropy. The random technique is used to test the model's effectiveness. Dropout is used to avoid overfitting while training the model. In the Decision Layer, these neurons were utilized to predict classes.

The steps to detect Coronavirus infections in CT images:

Step 1: Input the CT image

Step 2: Convert the input images to RGB format.

Step 3: Resize the image into (192×192).

Step 4: CNN model we choose layer sizes = [16, 32, and 64], dense layers = [1, 2], and 2D Convolution layers = [1, 2, and 3].

Step 5: The filter size is 2×2 for convolution.

Step 6: The convolutional layer is thereafter accompanied by the use of the activation function RELU. The activation function in the proposed neural network eradicates unnecessary dimensions, for example, negative values. The Rectified Linear Unit ReLU is an equation. It is an activation function that takes a non-linear shape of the form of the positive proportion of its arguments and is shown in Figure 5.

Step 7: Subsequently, the Max Pooling technique is used with a filter size of 2×2.

Step 8: Implement the Flatten operation, which involves vectorization, to transform a 3D matrix into a 1D vector.

Step 9: The SoftMax activation function is used to categorize the test image as either COVID or non-COVID. The SoftMax function is used as the activation function in the output layer of neural network models that are specifically tailored to predict a multinomial probability distribution. The SoftMax function is often used as the activation

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function for jobs that require the classification of several classes. The probability will range from 0 to 1. The SoftMax function enables the conversion of the output into a probabilistic representation.

Step 10: The training process utilizes the ADAM optimizer with a batch size of 100, a maximum of 30 epochs, and a loss function based on binary cross-entropy.

Step 11: The dataset is partitioned in an 80:20 ratio, with 80% of the data designated for training and 20% designated for testing.

Step 12: The evaluation measures are accuracy, precision, sensitivity (recall), specificity, and F-measure.

Step 13: After the model has undergone training, predicting whether a person is infected with Coronavirus or not becomes a straightforward task.

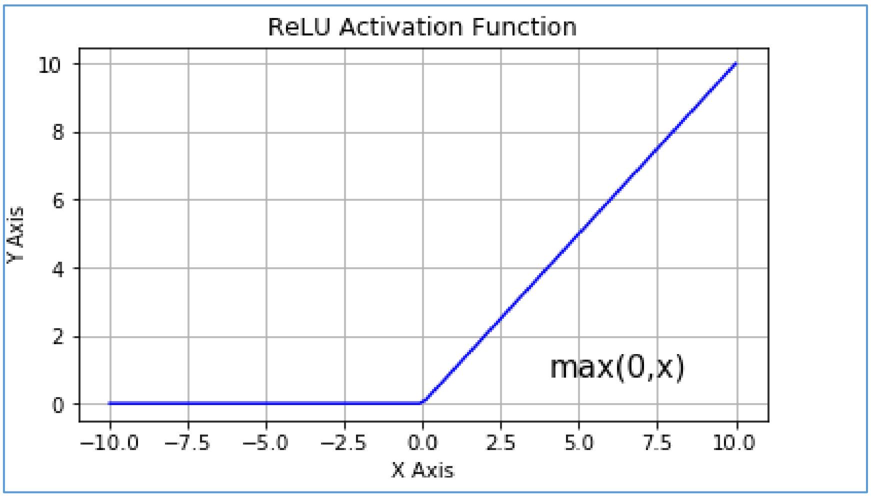

Fig 5. *The Rectified Linear Unit (ReLU)*

4. Results and Discussion

4.1 Evaluation Methods

The evaluation approach is an essential element used to evaluate the efficacy of the provided model. The medical image analysis system is assessed based on conventional criteria including accuracy, recall, precision, and the F1-Score. The computation of these methods relies on a confusion matrix.

Accuracy refers to the proportion of properly identified instances in relation to the whole dataset [18].

$$\text{Accuracy} = (TP+TN)/(\text{ Total number of testing data }) \qquad (1)$$

Sensitivity (Recall): This metric represents the ratio of correctly identified positive cases, namely the accurate identification of persons who are sick with a certain virus. (true positive proportion).

$$\text{Sensitivity} = TP/(TP+FN) \qquad (2)$$

Specificity refers to the ability of a test to accurately identify healthy persons who do not have any infection, measured as the percentage of true negatives.

$$\text{Specificity} = TN/(TN+FP) \qquad (3)$$

Precision: Refers to the precision in forecasting the percentage of COVID-19 cases that are positive[23].

$$\text{Precision} = TP/(TP+FP) \qquad (4)$$

F-measure(Score): The F-measure is a significant metric for assessing class imbalance in test data. It combines precision and recall measurements.

$$\text{F-measure(Score)} = 2 \times [((\text{precision x Recall}))/((\text{Precision} + \text{Recall}))] \qquad (5)$$

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True Positive TP refers to the rate at which the percentage of cases are correctly recognized as COVID-19. False positive FP refers to the rate at which cases of COVID-19 are incorrectly identified as positive. The accurate categorization of the negative rate as normal is TN. FN refers to the rate at which positive cases are incorrectly categorized as negative (normal).

4.2. Description of the research results

The proposed method was effective in categorizing two dataset groups. The first will be COVID-19, while the second will be Non-COVID. After training the model for 100 epochs, we calculated Accuracy, Recall, Specificity, Precision, and the F-measure, which we used to create the Accuracy and validation loss curves (Figure 6). The F-measure, Accuracy, Sensitivity, and Precision have all been evaluated on the testing data. The prefix Training indicates that the parameter was computed using training data (e.g., Training-Accuracy), whereas the prefix Testing indicates that it was calculated using testing data (e.g., Testing-Accuracy). Accuracy and loss become more significant with each epoch, as shown in Figure. Because these metrics should be higher, this is a success for the model. Figure 5 shows that the initial accuracy for training data was around 65% and for testing data was around 66%.

The values, on the other hand, incrementally increase with each period. At the 30th epoch, Training-Accuracy had almost achieved its highest level value (99.19 %) and Testing-Accuracy had reached 97%. Testing-value Accuracy is quite suitable. For each epoch, the loss has been calculated and the values have been saved. In comparison to the training loss computed, the dataset is rather modest than the testing dataset, which has a value of virtually zero. The accuracy improves with each epoch, and the loss of training data decreases. Initially, Testing-accuracy was higher than Training-accuracy, but as the gradually increased, Training-accuracy grew larger. The final results of Precision are 98%; Sensitivity makes the final value 98%, and the F-measure value is 97%.

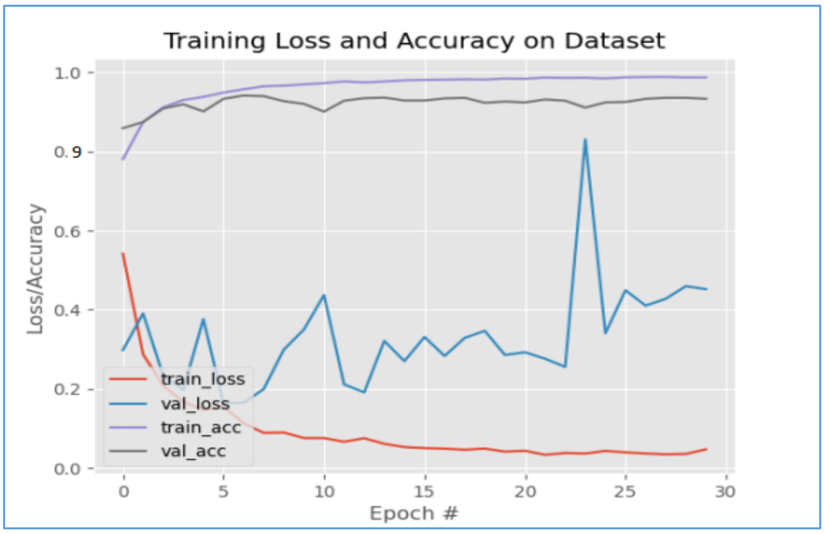

***Fig 6** . Different evaluation parameters of the model.*

The confusion matrix is visually shown in table 1, with values 72, 1, 3, and 73 showing True Positive TP, False Negative FN, False Positive FP, and True Negative TN values sequentially. These values determine the accuracy, recall, specificity, precision, and F-measure. Applying equations 1 to 5, we obtain the following values for our model's accuracy, sensitivity, specificity, precision, and F-measure: 97 %, 98 %, 96 %, 98 %, and 97 % respectively.

Table I. Confusion Matrix of the Model.

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True Label	Non-COVID19	COVID19
Non-COVID19	1	72
COVID19	73	3

Predicted label

TP=72 ,FN=1,FP=3,TN=73

Sensitivity (Recall) = TP/(TP+FN)

Sensitivity = (72(72+1)) *100 =98%

Specificity = TN/(TN+FP)

Specificity = 73(73+3))*100 = 96%

Precision = TP/(TP+FP)

Precision = 72(72+3))*100 =96%

F-measure(Score) = 2 × [((precision x Recall))/((Precision + Recall))]

F-measure(Score) = 2 × [((96 x 98)/((96 + 981))] *100 =97%

Table II compares our findings to those of others [20] and [24]. The proposed is more accurate and sensitive. As a result, our model is 12.3 % and 4.52 % more accurate than [20] and [24]. This model already has a higher sensitivity than [20] and [24], which are about 21.8 % and 3.83 %, respectively. It has a higher specificity of 6.42 % than [24]. When these parameters are compared, we can conclude that our model is superior to these two in terms of a CT scan image classification COVID-19 or non-COVID.

***Table II** .Comparison with the recent outcomes.*

Study	Accuracy	Specificity	Sensitivity
Our work	99%	96%	98%
[24]	92.48%	89.58%	94.17%
[20]	84.70%	N/A	76.20%

5. Conclusion

COVID-19 is a global pandemic caused by a highly contagious virus. This study employs a deep-learning technique to identify and diagnose COVID-19, with the aim of assisting healthcare practitioners. Deep learning using Convolutional Neural Networks CNN in CT scans provide dependable, streamlined, and accurate solutions for medical diagnostics, and ongoing research is being thoroughly assessed. Future research should focus on exploring the advancement of AI techniques and the manufacturing of medications for COVID-19 treatment, and the use of AI technology in research to mitigate the transmission of COVID-19. Classifying the illness based on its strain, such as COVID-19 or COVID-20, and determining if the new strains have similar effects as strain 19. Additionally, categorizing the disease based on the stage and rate of lung infection. Ultimately, enhancing the AI methodologies to facilitate the more efficient administration of overall well-being. Using artificial intelligence techniques to classify COVID-19 disease, and using digital lung images to classify whether the lung is infected or not by using deep learning algorithms.

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Conflicts of Interest

The authors have no conflicts of interest to declare.

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