

## RESEARCH ARTICLE



# Hybrid Deep CNN Model for the Detection of COVID-19

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OPEN ACCESS

Received: 07-09-2022

Accepted: 22-09-2022

Published: 02-11-2022

**Citation:** Sen AP, Rout NK, Pradhan T, Mukherjee A (2022) Hybrid Deep CNN Model for the Detection of COVID-19. Indian Journal of Science and Technology 15(41): 2121-2128. <https://doi.org/10.17485/IJST/v15i41.1421>

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**Funding:** None

**Competing Interests:** None

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Published By Indian Society for Education and Environment (iSee)

ISSN

Print: 0974-6846

Electronic: 0974-5645

## Abstract

**Objectives:** To propose a model which will pre-process the dataset for the removal of any noise before the training of the network. **Methods:** Reported literature does not focus on the pre-processing of the dataset before the training of the network. A noise removal scheme called Probabilistic Decision Based Adaptive Improved Trimmed Median Filter (PDAITMF) is implemented as a pre-processing tool before the developed model. The PDAITMF de-noises the dataset. **Findings:** This supports an effective learning process by the model. The model is trained, validated, and tested with the respective dataset. Accuracy of 0.9401 is achieved without the implementation of PDAITMF, while an accuracy of 0.9841 is achieved when the model uses the dataset processed by PDAITMF. Synchronization is also established between the training and validation graph which seems to be missing when the model uses the dataset without processing through PDAITMF. **Novelty:** A sharp improvement in accuracy is noted which establishes the effectiveness of the noise removal scheme before the Deep Learning model. The technique may be used to improve the detection accuracy of other acute diseases.

**Keywords:** Deep Learning; Transfer Learning; COVID19; Noise removal; COVID 19 detection

## 1 Introduction

Covid-19 is an epidemic sickness that has become a worldwide threat to mankind. It's crucial to distinguish between covid-19-infected and healthy people<sup>(1,2)</sup>. The novel coronavirus began as a throat infection, and victims began to have trouble breathing. The covid-19 disease is a slumbering foe that no one can defeat. Individuals affected with Covid-19 must be isolated, undergo proper checks, and take necessary precautions to safeguard healthy persons<sup>(3)</sup>. After getting into contact with covid-19 infected people, this virus follows a chain mechanism that spreads from one individual to the next<sup>(4)</sup>. The diagnosis of this epidemic relies heavily on hospital workers, nurses, doctors, and

health support. Many other techniques have been implemented to mitigate Covid-19's impact. Medical imaging<sup>(5)</sup> can be used to assess and evaluate the impacts of covid-19. With the use of CT<sup>(6)</sup> and chest X-ray scans<sup>(6-12)</sup>, healthy individuals and Covid-19 infected patients could be studied in parallel. We gathered CT scans of normal and Covid-19 affected individuals from multiple sources, preprocessed them, and then used them in our model to contribute to a Covid-19 study. CNN, a deep learning technology with a vast scope<sup>(13-15)</sup>, is used to analyze the data that has been acquired. This research focuses on using CNN models to classify COVID-infected subjects' chest CT scans. Efforts have been done to draw a comparison with earlier work in the area and explore prospective task models that might be evaluated further to demonstrate their utility in real-world circumstances.

With the use of X-ray scans, the studies recommend a framework centered on Capsule Networks to detect Covid-19 (i.e., COVIDCAAPS) disease<sup>(16)</sup>. To tackle the issue of class imbalance, various convolution layers and capsules have been used in this suggested study. They demonstrated COVIDCAPS' satisfactory performance on a lesser number of trainable parameters in the experimental study. The authors mentioned the analyzed trained model, which is open source and freely accessible on Github<sup>(13)</sup>. As a result, they determined that the suggested framework has a 95.7 percent, 90 percent sensitivity, and 95.80 percent specificity while using less trainable parameters. The authors of<sup>(16)</sup> studied three patients who got initially infected by Covid-19 in France. Two of them were identified in Paris, while the third was identified in Bordeaux. They were all in Wuhan, China, before getting into connection with Covid-19 infections. The report in<sup>(17)</sup> highlights how infected people were treated with chest X-rays.

In<sup>(18)</sup>, the author addressed what types of measures hospital staff must adopt to reduce the likelihood of healthy individuals and what precautions must be taken when caring for covid-19 affected individuals. The authors examined the etiologic epidemic in Wuhan, China, in<sup>(19)</sup>. They also highlighted the issue of the epidemic's actual cause. They assess the impact of traveling (by commercial or air) on covid-19 throughout this research.

The authors of<sup>(20)</sup> examined the chest CT scans of 21 covid-19 individuals in Wuhan, China. They were particularly interested in the effects of covid-19 illness on human lungs. The authors in

<sup>(21)</sup> presented a COVID-RENet model for extracting features (e.g., edge and region-based) and using CNN for classification. On an available dataset of Covid-19, they employed 5-fold cross-validation. This proposed method is primarily intended for use by a medical practitioner in the early detection of Covid-19-infected people. With the VGG19 architecture, Apostolopoulos and Bessiana were able to classify COVID-19 with 97.8% accuracy<sup>(22)</sup>. COVID-19, no-finding, and pneumonia were classified with 87% accuracy by Ozturk et al.<sup>(10)</sup>.

The research so far highlighted the utilization of CT scans and their importance to expedite the detection process of COVID-infected patients. The model so far proposed uses either a deep CNN model or a trained model to detect the disease. The major issue that is found in the reported models is the unavailability of preprocessing technique for data denoising. The CT scans mostly contain impulse noises induced by a drop in the number of photons required to create the image, which is frequently related to a decrease in the X-ray tube current-ampereage (mAs)<sup>(23)</sup>. To improve the accuracy and obtain an optimized detection result, a robust noise detection technique may be applied before a deep learning model. The paper is focused to develop such a model which resolves the issue mentioned above to obtain an improved result that will help the medical practitioners to segregate the COVID-infected patients more accurately for further medical treatment.

This report is divided into several modules, such as in part 2, we discussed the complete methodology explaining the construction of a dataset along with the discussion of the model. In addition, section 3 discusses the results obtained by the model. The work is then concluded in section 4.

## 2 Methodology

### 2.1 Data Creation

The COVID-CT dataset's creation is detailed in this section. At first, 1260 preprints of COVID-19 were obtained from medRxiv1 and bioRxiv2 and displayed till May 15th. A considerable percentage of these preprints describe COVID-19 cases. CT images are accompanied by subtitles that explain the clinical results. PyMuPDF3 was used to remove the low-level structure data from preprint PDF files and locate all embedded figures. We were also able to distinguish inscriptions associated with figures based on the structure data. We begin by physically selecting all CT scans based on these extricated figures and subtitles. Further, the relevant inscription for each CT image is checked to verify if it is correct for COVID-19. If the subtitle was insufficient to make a decision, we located the content exploring this figure in the preprint to make a decision. We also divided each figure that has several CT scans as sub-figures into single CTs. Finally, 369 CT images were identified as COVID-19 positive samples after removing several of the low-quality scans. The sizes of these CT images vary. All CT scans have been reduced to 224 X 224 pixels. These scans were taken from 171 different patient instances. A few examples of COVID-19 CT scans are shown in

Figure 1. A total of 369 non-COVID CT scans with pneumonitis indications were added to the dataset.

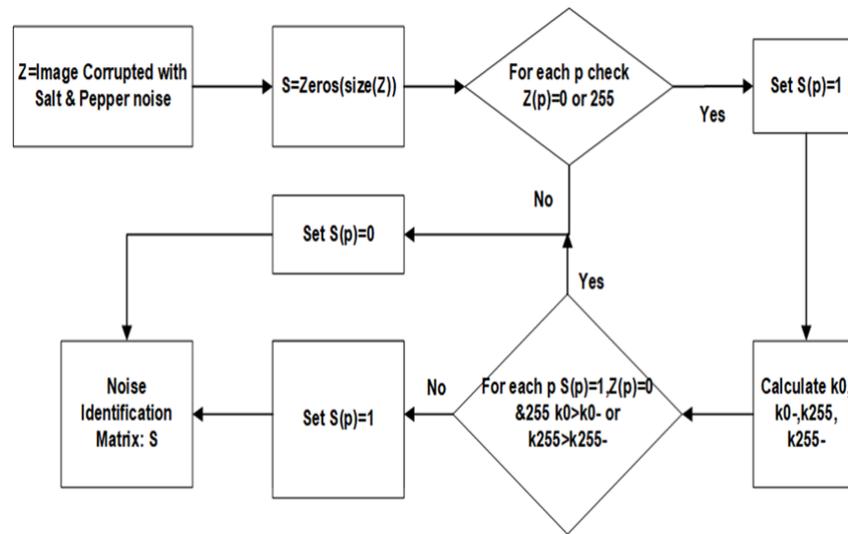


Fig 1. Noise Detection

## 2.2 Proposed Model

The proposed model is developed in this part based on two aspects

- i. Implementation of the noise removal algorithm
- ii. Implementation of the deep learning model for the detection of COVID-19

### 2.2.1 Implementation of the Probabilistic Decision Based Adaptive Improved Trimmed Median Filter (PDAITMF)

The collected dataset has noisy pixels, resulting in poor image quality. The majority of the noise in the dataset is impulsive. As a result, PDAITMF<sup>(24-28)</sup> is chosen and presented in Figure 1-2 to eliminate the noisy pixel parts. This preprocessing of the dataset by removing the noise will improve the learning capability of the model. Good learning of the features will further improve the accuracy to detect the disease. Three algorithms are used to create the algorithm:

- i. Noise Detection Module
- ii. Improved Trimmed Median Filter (ITMF)
- iii. Patch Else Improved Trimmed Median Filter (PEITMF)

### 2.2.2 Implementation of the Transfer Learning Technique for the detection of COVID-19

The proposed model for COVID-19 detection incorporates the VGG-19 framework. The processed dataset is fed to the dataset model. The network has a depth of 19. A convolutional filter with 64 in number and a size of 3x3 is used. The pooling layer is used after the convolution filter layers. Figure 3 depicts the model's whole construction. Data augmentation is used to expand the dataset so that more samples could be made available for the model to learn the features effectively. It is a strategy that uses techniques like cropping, padding, and flipping to enhance the number of data points available. It makes the model more resistant to some alterations and, as a result, helps to prevent overfitting. The output layer uses the Softmax activation function, while the remaining layers employ the Relu function. ReLU is used to increase the network's non-linearity, prevent over-fitting, and speed up the training process. At the output, which has only two classes, a binary cross-entropy loss function is applied. The block diagram is shown in Figure 3.

## 3 Results and Discussion

The development and simulation are performed in the Python platform using Spider 3.1. The system has GTX 1080T graphics processor, and the cuDNN-v7.1 deep learning library is used to speed up computational efficiency. Using 738 CT images, the binary classification model is trained to predict whether a CT image is COVID or non-COVID. There are 369 COVID and

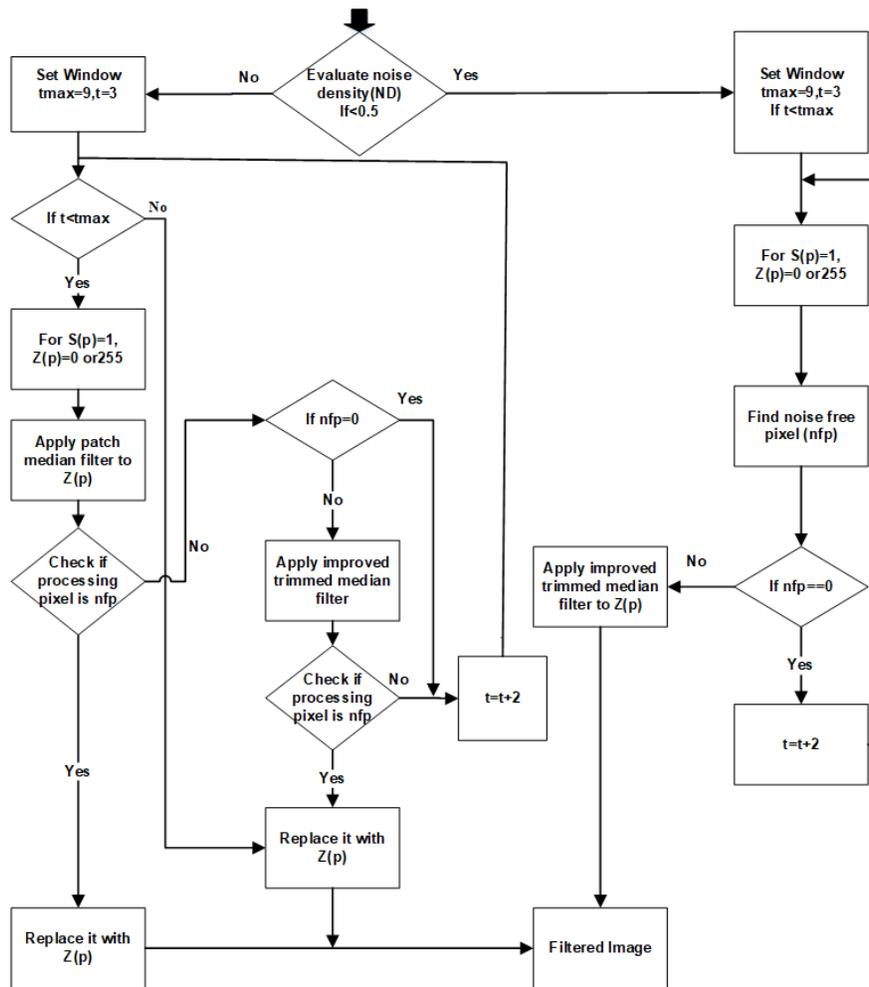


Fig 2. Noise Removal

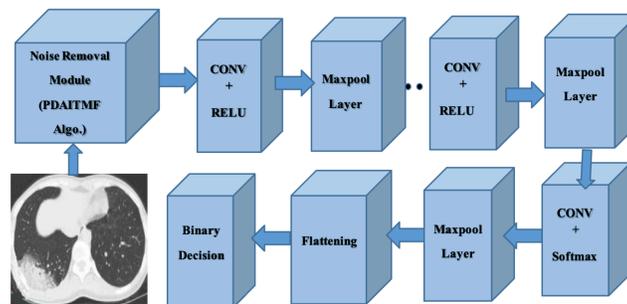


Fig 3. Block diagram of the Covid-19 detection network along with PDAITMF

369 non-COVID CT scans in the dataset. With 66 percent, 17 percent, and 17 percent, respectively, the dataset is divided into three sets: training, validation, and test. All of the photographs have been scaled to 224 x 224 pixels. The validation set is used to optimize the hyperparameters. The Adam optimizer was used to optimize the network's weight parameters. The batch size is set at 32. Figure 4 shows the produced graph after the network has been trained without using the noise removal module. In this training phase, the dataset is fed directly without applying the de-noising algorithm. The training accuracy of the model is 98.6, while the validation accuracy is 79.8. The training loss of the model is 0.0524, whereas the validation loss is 0.2975. Figure 5 depicts the graph obtained after the model is trained using the processed dataset through the noise removal module. The training accuracy of the network is 98.46, while the validation accuracy is 94.29. The training loss of the network is 0.0536, whereas the validation loss is 0.2010.

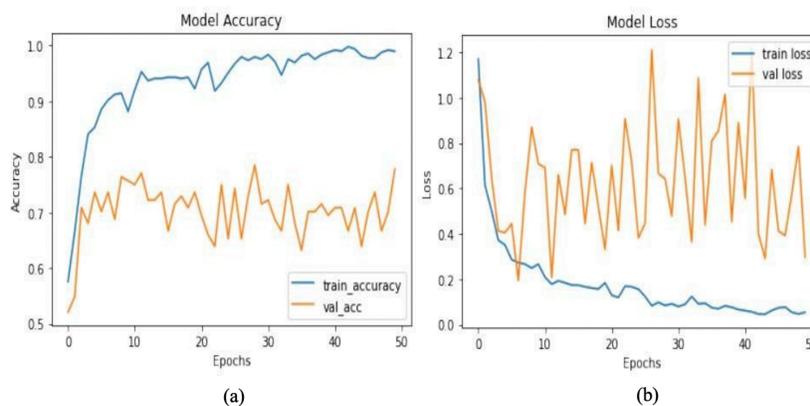


Fig 4. Model without using PDAITMF (a) training accuracy and validation accuracy, (b) training loss and validation loss

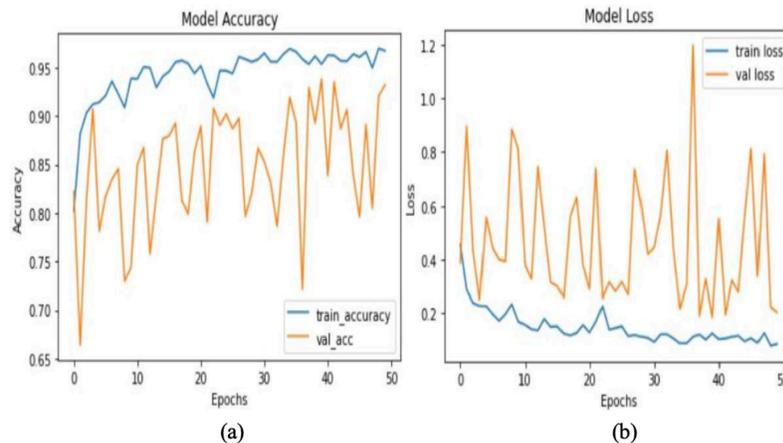


Fig 5. Model with using PDAITMF (a) training accuracy and validation accuracy, (b) training loss and validation loss

The findings show that implementing the PDAITMF module, receives noise-free data for training, the accuracy attained over the validation set improves and the gap between training and validation sets decreases. The model learns the characteristics well, and when validated with the new set, the model has considerably less difficulty predicting COVID occurrences than the model without the PDAITMF module. The loss there in the model is reduced to a minimum. In comparison to the model without the PDITMF module, the validation loss in the model with the PDITMF module is lower. Figure 4 b and Figure 5b indicate the loss in the models. It can be seen and examined in Figure 4- Figure 5 that including the PDAITMF module in the model improves the model's efficiency in predicting COVID1-19 instances. A confusion matrix can be used to examine the capability of the proposed COVID-19 classification model. A confusion matrix is used to calculate metrics like accuracy, sensitivity, specificity, precision, and F1 score. It's a table with four separate sets of expected and actual values in it. Figure 6 shows the confusion

matrix parameters and Figure 7 shows the obtained confusion matrix.

		Predicted Values	
		Negative	Positive
Actual Values	Negative	<b>TN</b>	<b>FP</b>
	Positive	<b>FN</b>	<b>TP</b>

Fig 6. Confusion Matrix

		Predicted Values	
		Negative	Positive
Actual Values	Negative	<b>61</b>	<b>2</b>
	Positive	<b>0</b>	<b>63</b>

Fig 7. Obtained Confusion Matrix

TP (True Positive): The actual data has a positive outcome and the model also predicts a positive outcome. So it's a true positive.

TN (True Negative): The actual data has a negative outcome and the model also predicts a negative outcome. So it's a true negative.

FP (False Positive): (Type 1 Error) The actual data has a negative outcome while the model predicts a positive outcome. So it's a false positive.

FN (False Negative): (Type 2 Error) The actual data has a positive outcome while the model predicts a negative outcome. So it's a false negative.

Now the performance metrics can be calculated as follows:

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

$$\text{Sensitivity} = \frac{(TP)}{(TP + FN)} \tag{2}$$

$$\text{Specificity} = \frac{(TN)}{(TN + FP)} \tag{3}$$

$$\text{Precision} = \frac{(TP)}{(TP + FP)} \tag{4}$$

$$F1 \text{ Score} = 2 * \frac{(\text{Recall} \times \text{Precision})}{(\text{Recall} + \text{Precision})} \tag{5}$$

$$\text{Recall} = \frac{(TP)}{(TP + FN)} \tag{6}$$

$$\text{False Positive Rate (FPR)} = \frac{(FP)}{(FP + TN)} \tag{7}$$

$$\text{False Negative Rate (FNR)} = \frac{(FN)}{(FN + TP)} \tag{8}$$

$$\text{False Discovery Rate (FDR)} = \frac{(FP)}{(FP + TP)} \tag{9}$$

Table 1 shows the accuracy, sensitivity, specificity, precision, recall, F1 Score, FPR, FNR, and FDR performance measures with PDAITMF and Without PDAITMF

**Table 1.** Performance metrics

Performance Metrics	Without PDAITMF	With PDAITMF	Percentage Change	Remark
Accuracy	0.9436	0.9841	4.29%	Improved
Sensitivity	0.9211	1	8.56%	Improved
Specificity	0.9673	0.9682	0.093%	Improved
Precision	0.9512	0.9692	1.89%	Improved
Recall	0.9874	1	1.27%	Improved
F1 Score	0.9624	0.9843	2.27%	Improved
FPR	0.0512	0.0317	38.08%	Minimized
FNR	0.0161	0	100%	Minimized
FDR	0.0509	0.0307	39.68%	Minimized

By multiplying the obtained parameters by 100, they can be expressed in percent. The accuracy was found to be 98.41% with PDAITMF which was 94.36% without PDAITMF. With a sensitivity of 1 and a specificity of 0.9682, the model with PDAITMF is quite effective in predicting COVID-19-positive patients in comparison to those without PDAITMF. The sensitivity and specificity parameters are notable, as they establish the model’s ability to accurately estimate COVID-19 cases. The false-negative value is zero, while the false-positive parameter is two, according to the confusion matrix. A single false-negative forecast can have a significant impact on society, just as a single COVID- 19 patient can transmit the disease quickly. As a result, the model with the noise removal module shows itself as a viable option for treating the deadly virus. The precision parameter acquired is especially noteworthy, given the little difference between sensitivity (recall) and precision. The model’s F1 Score improves much more as a result of this. The efficiency may be improved much further by expanding the dataset and incorporating some fusion techniques to reduce the false positive parameter even more. The outcome is encouraging, but because the algorithm is designed to identify lethal COVID, there is room to improve. In the future, new optimizing techniques can be applied to increase the outcome for far better results.

## 4 Conclusion

For the identification of COVID confirmed samples, the developed framework employs noise removal techniques, transfer learning, and data augmentation techniques. The dataset is created using publicly available data and then processed by running it through PDAITMF to remove noise. In around 9 out of 10 situations, the model correctly recognizes COVID positive cases. Although the accuracy on the training set is impressive, the accuracy on the validation set might be enhanced even more for even better results. The acquired data was of poor quality, with some unwanted distortions that were dealt with as best as possible. The model with PDAITMF outperforms in terms of performance metrics in comparison to the model without PDAITMF. The simulation results prove and lay a path for further research in optimizing the model accuracy by taking care of the noise factor in the dataset. Various noise removal strategies could be used in conjunction with other deep learning models or their variants to improve the performance even more. More precision is essential because the model is developed for the present epidemic, which is extremely dangerous to humans. The model would be improved further in the future with the use of more hybrid methods for clearly better prediction effectiveness.

## 5 Conflict of Interests

The process of writing and the content of the article does not give grounds for raising the issue of a conflict of interest.

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