INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

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OPEN ACCESS

**Received:** 25-04-2024

**Accepted:** 22-08-2024

**Published:** 05-09-2024

**Citation:** Patil PB, Patil NJ (2024) Prediction of Covid-19 From Lung CT Images Using Fine-Tuned Deep Learning Models. Indian Journal of Science and Technology 17(35): 3678-3687. https://doi.org/10.17485/IJST/v17i35.1402

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**Funding:** None

**Competing Interests:** None



Published By Indian Society for Education and Environment (iSee)

**ISSN**
Print: 0974-6846
Electronic: 0974-5645

# Prediction of Covid-19 From Lung CT Images Using Fine-Tuned Deep Learning Models

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## Abstract

**Objectives:** This research article's principal objective is to improve and create a fully automated methodology for the recognition and diagnosis of infections in the lungs Computed Tomography pictures using pre-trained neural network architectures. **Methods:** The proposed model have employed a total 746 CT scan sample which is openly accessible, comprising 349 scans who tested positive for COVID-19 and 397 scans that are either healthy or show different respiratory illnesses. Convolutional neural networks (CNNs) with four different architectures—InceptionV3, ResNet-50, Xception, and VGG19 are employed and refined based on the intended objective. After then, in order to increase performance metrics, an ensemble technique employing the Adam optimizer have developed. **Findings:** These outcomes demonstrated the utility of Artificial intelligence in identifying COVID-19 instances. When measured against every other deep learning model the N-VGG-19 revealed an accuracy of 90%, indicating its better performance. **Novelty:** Using the Adamax optimizer and data augmentation approach, The proposed method have contributed a thorough assessment of many already trained neural network modules such as ResNet50, InceptionV3, N-VGG19, and Xception.

**Keywords:** Artificial intelligence (AI); COVID-19; Convolutional Neural Network; CT Scan; Deep Learning

## 1 Introduction

Global healthcare is seriously threatened by the coronavirus along with various versions, which are still spreading around the world [1]. Early diagnosis of this disease becomes essential. The well-known symptoms of this virus are fever, dryhack, and fatigue. Some of the patients may suffer with a sore throat, headache, loss of smell or test, running nose [2]. The most common examination method for determining its identity is reverse-transcription polymerase chain reaction (RT-PCR) testing [3]. Chest computer tomography is nonetheless presumably more practical, quick, and trustworthy than RT-PCR [4]. With the use of chest computer tomography (CT) scans, it became possible to identify the anatomical characteristics of lung lesions associated with the COVID-19. Most of the hospital offers chest CT scans of COVID-19 patients, which can be useful for early diagnosis of the disease [5]. But to evaluate the test results requires a radiology expert. Even an experienced radiologist also takes several minutes to analyse the CT images [6]. During the pandemic epidemic, there is a significant dearth of competent radiologists, making it difficult to quickly identify patients who may be affected. In the early, stage ground glass opacities are (GGO) common CT result [7]. Consolidation of air space occurs during the advanced stage and broncho vascular thickening in peak stage [8]. Recently, deep learning techniques have made significant advances in healthcare data analysis as well as automation due to their capacity to extract helpful information from available datasets [9]. There are especially trained architectures present in deep learning that categorize inputs into the many categories needed by users [10]. They are used in the medical profession to identify cardiac abnormalities, tumor detection from image analysis, diagnosis of cancer, and a variety of other applications [11]. With an accuracy of 89%, the N-VGG-19 with Adamax optimizer model outperformed the others in identifying images as either COVID-19 or not.

The proposed model, which is built on convolutional neural network (CNN) can be useful in differentiating CT scan images as covid19 positive or negative. Convolutional neural network consists of various architectures which can be trained to classify inputs into various classes [12]. Every task requires the development of objectives that help to address the problems and challenges facing the organization. Artificial intelligence and deep learning have been applied in a multitude of experiments and development initiatives related to medical imaging, specifically in the field of diagnostics employing computed tomography (CT) images. In the deep learning domain, deep neural networks (DNNs) are constructed by stacking layers of artificial neurons [13]. Deep learning networks have several layers that transform data into decision making. CNN is a type of deep neural network with widely used applications utilized in images and videos.

CT has proven to be helpful for COVID-19 patient diagnosis during the pandemic. Obtaining sufficient large-scale data from publicly available datasets to train deep-learning models for uncommon medical disorders such as COVID-19 might be difficult [14]. As a result, transfer learning is used to strengthen the proposed systems. Lung scanning tools, which involves chest X-ray CT and MRI, imaging are extremely effective and economical diagnostic radiology techniques for lung disease [15]. Despite highly skilled and experienced radiologists, it can be challenging to separate COVID-19 from pneumonia utilising X-ray pictures since both conditions have similar location characteristics. Numerous research have concentrated on COVID-19, pneumonia analysis, and diagnosis using multiple approaches [16]. The majority of healthcare apps are in greater demand due to their notable characteristics, which are supported using deep learning, machine learning, and artificial intelligence (AI). The research work suggested by [17] uses an effective image sorting technique that employs effective Net with filtering to boost the resolution of the pictures in order to detect COVID-19 utilizing CT images. Many transformation techniques work fairly well on Effective Net, including CLAHE, Wavelet, Laplace, and Adaptive Gamma.

For COVID-19 identification, the authors [18] provided a number of deep transfer models, fusion classifiers, and deep pattern composing techniques. Toğaçar et al. [19] conducted a study to examine the relationship between COVID-19 pneumonia clinical symptoms and chest CT results. The clearest signs of COVID-19 infection on the CT scan images were bilateral, peripheral ground-glass and consolidative lung opacities [20]. Since COVID-19 datasets are hard to come by, Zhao et al. [21] created the open-source dataset COVID-CT, which includes 463 non-COVID-19 CTs and 449 COVID-19 CT images from 216 individuals. Wang et al. [22] used 3D CT volumes to construct a deep learning-based software solution for automated COVID-19 identification on chest CT. On the basis of 630 CT images, an already trained UNet and a 3D neural network with deep learning were used to forecast the likelihood of COVID-19 infections.

### 1.1. Contribution of the work

The following are the contributions made in designing a system powered by deep neural networks for detecting infection in lungs using chest CT pictures.

- The suggested models can increase training speed and decrease the number of training images by utilizing the knowledge of a pre-trained network.
- This study focuses on reducing false positives and false negatives rates, as it is crucial for severe illnesses like COVID-19 and Pneumonia.
- Due to the less number of available COVID-19 CT images, the problem of over-fitting arises, which is reduced using batch normalization and dropout.
- This study focuses on lowering down on the time it takes to identify COVID-19.
- Recall, accuracy, precision, and F1 score are among the evaluation metrics used to assess these fine-tuned and ensemble models.

## 2 Material and methods

Recent years have seen a number of promising uses for deep learning. It is useful for researchers in various fields. Due to its excellent accuracy, everyone now prefers CNN over other layers for image sorting. The COVID-19 CT database was made up of images of patients whose COVID-19 testing results had also been verified by RT-PCR. The dataset includes 738 images that were downloaded from Kaggle. Out of 738 CT scan images, 349 images from 216 individuals were found to contain COVID-19, while 397 images belonged to patients who were not infected with the virus. In both the training and test sets, there were considerably more normal photos than COVID images in the research dataset, which also had relatively low data volume and imbalanced positive and negative samples. This can result in overfitting and inadequate post-training validation. In order to create new photos, we rotated, flipped, scaled, and altered the brightness of the original datasets using data augmentation techniques. Figure 1 illustrates the proposed method for diagnosis of COVID-19 using various fine-tuned models.

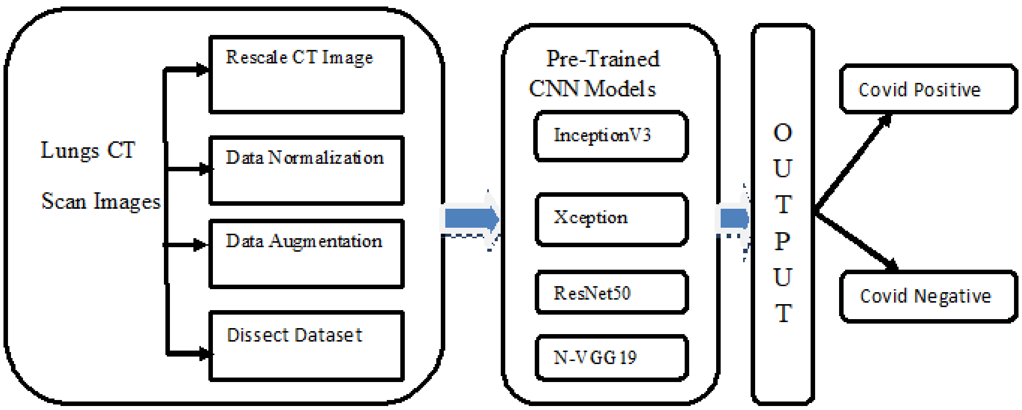


**Fig 1. Proposed method for diagnosis of COVID-19 using various Models**

### 2.1. Preprocessing

When working with image data, preprocessing an image is the primary and most important stage. To identify COVID-19 in chest CT scans, CNN is employed as a binary classification system. The input images are all resized to 224×224×3 to preserve uniformity since they are all various sizes. In order to train the model from scratch,a huge amount of samples must be required in order to learn the neural network. Since the majority of the COVID-19 database is much lower, it takes longer to create an effective model. As a result, the proposed models are created using the models that have already been trained and modified to recognise COVID-19.

### 2.2. Proposed methods

Using four distinct algorithms constructed from a deep convolutional neural network, the task of identifying individuals contaminated with the coronavirus employing CT has been carried out (VGG19, ResNet50, InceptionV3, and Xception). The suggested model used a transfer learning approach that leveraged the weight of the pre-trained models (ImageNet (Russakovsky et al. 2014)). Three elements make up the model's fundamental design: a prediction classifier, a collection of three layers that have been adjusted to meet researchers demands, and a pre-trained network. Some modifications are made to each model's architecture in order to obtain effective prediction performance. To be more precise, the suggested method used optimizers to meet categorization objective and added extra layers to the conclusion of each model's design. Each of the four created models' specifics are explained in the following subsections.

### 2.3. InceptionV3 model

Label Softening, Transformed 7 x 7 convolutions, with the addition of an auxiliary classifier to transfer label data lower down the network are some of the advancements in the Inception-V3 CNN network architecture. The fundamental design principle of the InceptionV3 architectures is to solve the problem of inappropriate variability in the positioning of significant areas in images under investigation by enabling the network to contain many kernel types onto the identical stage, thus ”widening” the scope of the network. Figure 2 illustrates the suggested procedure for COVID-19 identification with the Inception model with the addition of a dense layer.

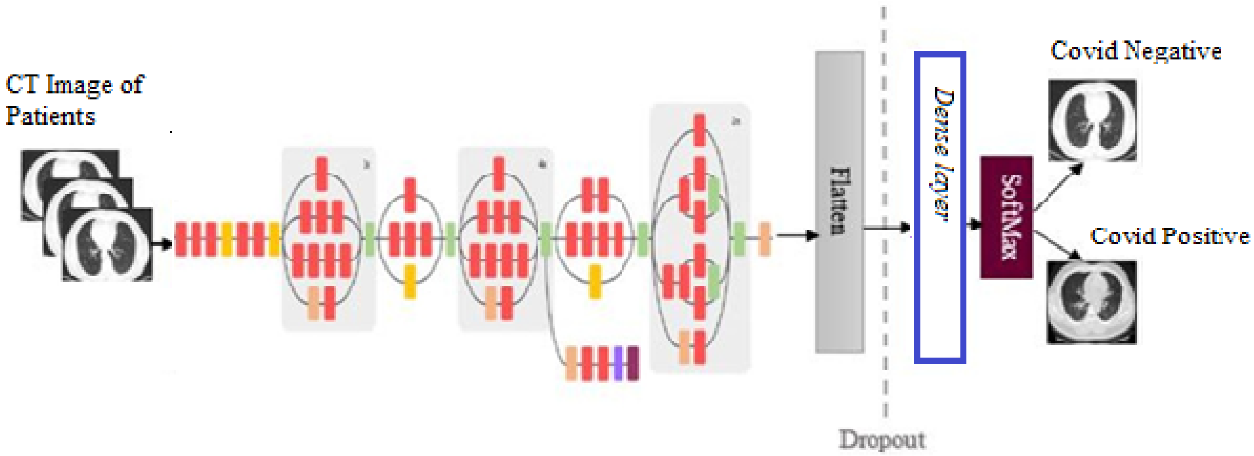


**Fig 2. Proposed Fune-Tuned InceptionV3 Model**

## 2.4. Xception

In the Xception architecture, the network’s feature extraction base consists of 36 convolutional layers. 14 distinct modules can be created from the 36 convolution layers. Following the removal of the first and last layers, every layer has an uninterrupted residual link surrounding it. Cross-channel correlations are obtained by converting the source image into spatial correlations across each end channel. Figure 3 illustrates the suggested technique for COVID-19 identification with the Inception model.

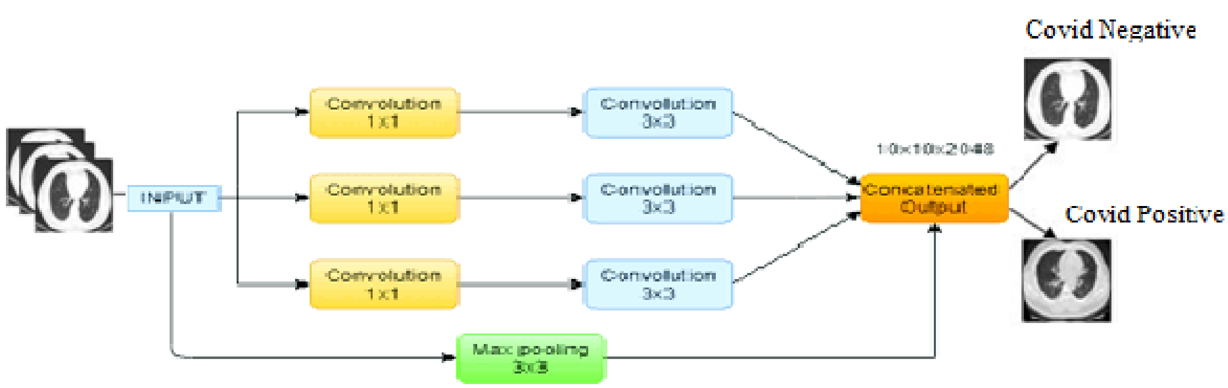


**Fig 3. Proposed Fune-Tuned Xception Model**

## 2.5. ResNet50

A ResNet design known as ResNet50 has 50 layers total. The ResNet50 architecture consists of many convolutional (conv) layers. Residual blocks constitute the majority of it. The primary benefit of residual connections in the ResNet design is that they maintain the information acquired during training and reduce the amount of duration required for model training by expanding the ability of the network. Figure 4 illustrate the suggested technique for identifying COVID-19 via the ResNet50 algorithm.

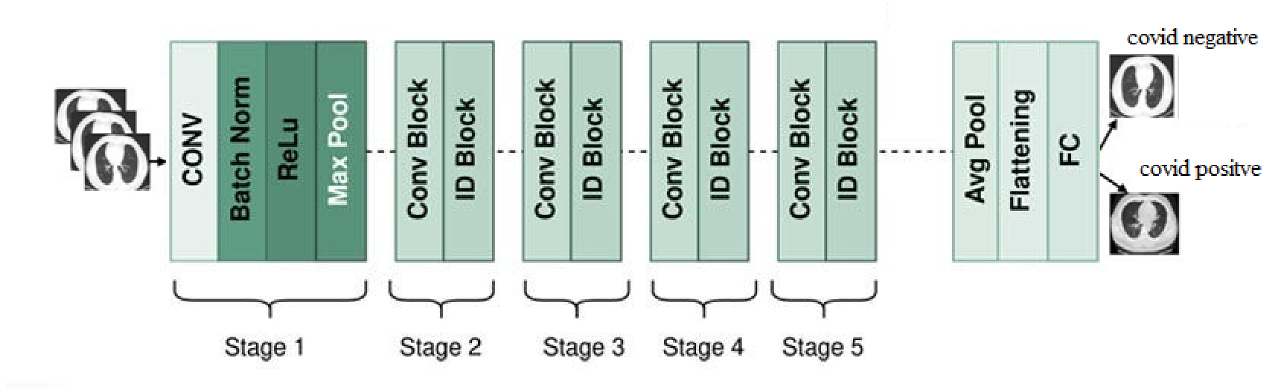


**Fig 4. Proposed Fune-Tuned ResNet50 Model**

## 2.6. N-VGG19

The N-VGG19 design has become one of the most recognized deep CNN techniques. VGG19 was offered by Simonyan and Zisserman from the Visual Geometry Group at the University of Oxford. Using a million photos over 1000 classes, the ImageNet repository is used to learn VGG19. The visual geometry group-19 (VGG-19) model, which has dimensions of 224×224×3, was fed the input photos. The model has 16 layers and 5 convolutional blocks in total. Every frame has two or three convolutional layers, five levels of max-pooling, three fully connected (FC) layers, and a softmax layer at the end. For binary classification, the softmax layer is replaced with the sigmoid layer. Two dense layers are added after the last convolutional layer. The suggested procedure for COVID-19 recognition utilizing the N-VGG19 concept is depicted in Figure 5.

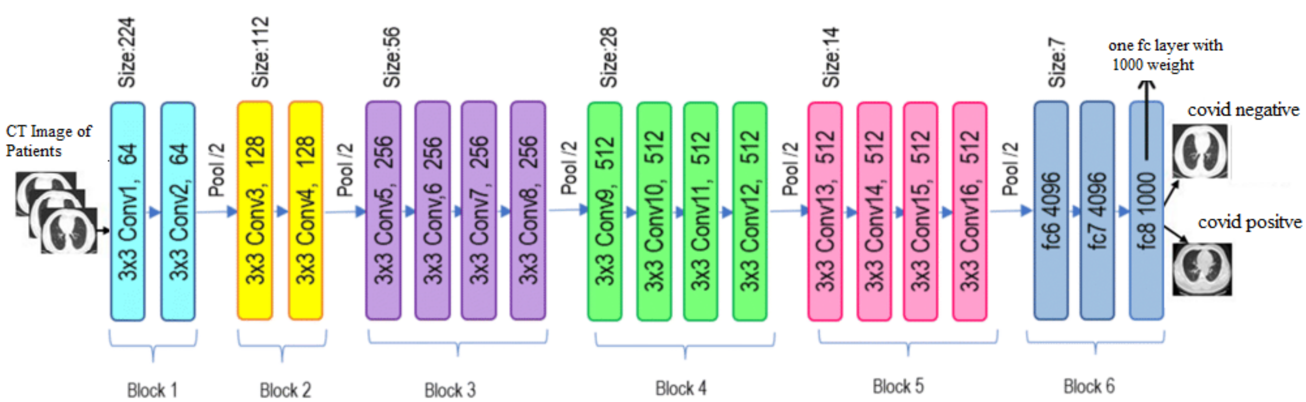


**Fig 5. Proposed Fune-Tuned N-VGG19 Model**

## 2.7. Training Procedure

The models were constructed using the NVIDIA Tesla T4 GPU, which is available in Google Colab. All the CNN models are trained using a batch of size 32. The sample images taken from the training dataset will be used to learn the classifier. The approach generates binary classification results, and computes loss using binary cross entropy, along with updating network weights using the Adam optimizer. System characteristics are retained in each epoch. To determine accuracy, the model classifies the validation set.

# 3 Results and Discussion

## 3.1. Potential Measures

### 3.1.1. Accuracy

One parameter to evaluate classification algorithms is accuracy. The percentage of correctly predicted events in relation to the entire sample size is what known as accuracy. An accuracy calculation formula is given below.

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

### 3.1.2. Recall

It is also known as true positive rate (TPR). A greater recall rate produces better prediction accuracy for the desired event and a lower chance of omitting a problematic instance. Equation (2) indicates recall expression.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

### 3.1.3. Precision

Precision is one statistic that may be employed to determine how well a machine learning algorithm is working. It is an indicator that assesses the model's consistency in identifying positive samples and pertinent information on the intended outcome. Equation (3) indicates the formula for precision.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

### 3.1.4. F1 Score

To mitigate the negative impact of accuracy, the F1 score is supplied as an integrated statistic when evaluating classifiers. Equation (4) is used to calculate the f1 score.

$$F1Score = 2\left(\frac{Precision * Recall}{Precision + Recall}\right) \tag{4}$$

**Table 1. Comparison of the proposed fine-tuned models with some state-of-the-art approaches**

| | **CNN Architectures** | **No of parameters (Million)** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1 Score (%)** | **Training Time (s)** | **Execution Time (s)** | **Remarks** |
|---|---|---|---|---|---|---|---|---|---|
| State of art Models | VGG19 + ResNet50 [23] | | 90.92 | 91.8 | 89.4 | | | | Due to feature fusion technique, the algorithm becomes more complex and takes more time to execute. |
| | VGG16 [24] | | 94.29 | | | | | | Relatively small dataset was used to learn the system. |
| | Efiicient2D (E2D) [25] | | | | | 81.2 | | | Improvement for addressing instability is necessary as CT images contain more redundant information. |
| | MobilneNetV1 [26] | | 97.44 | 97.58 | 75 | | | | The complexity of networks has escalated as a result of the parallel design. |

*Continued on next page*

*Table 1 continued*

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Proposed Fine-Tuned CNN Models | **InceptionV3** | 24 | 73 | 73.5 | 73.5 | 73.5 | 630 | 0.01749 | To achieve the desired computation efficacy, the duration of training needs to be kept to a minimum. |
| | **Xception** | 22.8 | 81 | 80.5 | 80.5 | 80.5 | 435 | 0.01353 | Relatively less no of training parameter are available. |
| | **ResNet50** | 23 | 72.5 | 71 | 89.5 | 69.5 | 245 | 27 | This model shows less accuracy. |
| | **N-VGG19** | 138 | 90 | 88.5 | 86 | 86.5 | 505 | 0.01289 | This model is having 12 milliseconds of classification time with more accuracy. |

## 3.2. Experimental Outcome

In the suggested research, the CNN layer models are assessed using the accuracy, precision, F1-score, and recall. When assessing a healthcare diagnostic method for COVID-19 recognition, these factors are useful. The accuracy and loss for each CNN model throughout the training and validation stages are illustrated in Figures 6, 7 and 8, and Figure 9. The fine-tuned ResNet50 model shows low-performing scores with a 72.5% accuracy rate when taking CT pictures. Higher false negative (FN) occurrences correspond with a weak recall score. Therefore, a significant amount for false positive (FP) outcomes is indicated by the poor accuracy ratio. This suggests that this framework identifies an extensive amount of FP and FN and, therefore, constitutes a predictor of poor abilities. The precision and recall rate for Xception remain the same for 100 epochs. It can be observed that the N-VGG19 algorithm outperforms all competing algorithms across every CT modality when one looks at every method independently.

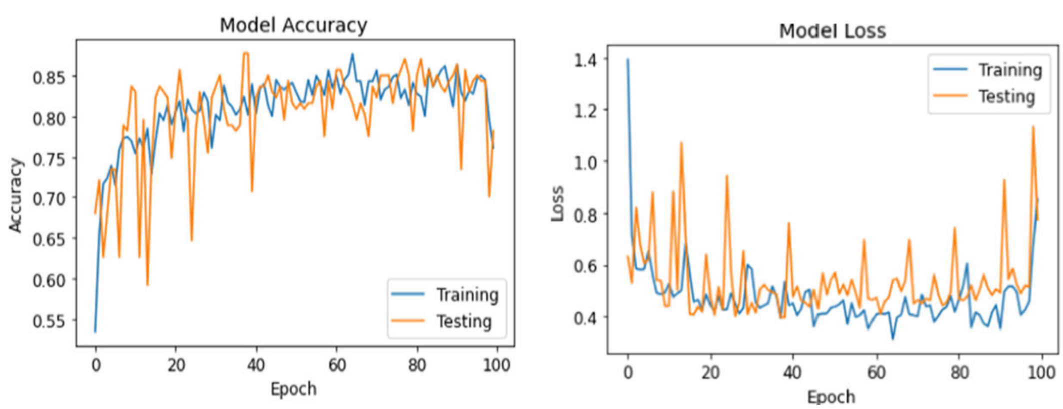


**Fig 6. Fine-Tuned N-VGG19 Models Performance Graph**

## 3.3. Time management

The amount of time the models required for training, testing, and execution, was examined as indicated in Table 1. The models VGG19, Resnet50, Inception V3, and Exception were used to measure speed and time gains. A model's "training time" is the amount of time it takes to learn a dataset, while testing time covers the process when a fully trained system's outcome is examined on a testing set. The algorithm is provided with one computed tomography image during the validation phase. the result showing if the patient has a coronavirus-positive infection or not. The execution time for each individual model won't vary if the measurements of the given CT scan photos remain identical.

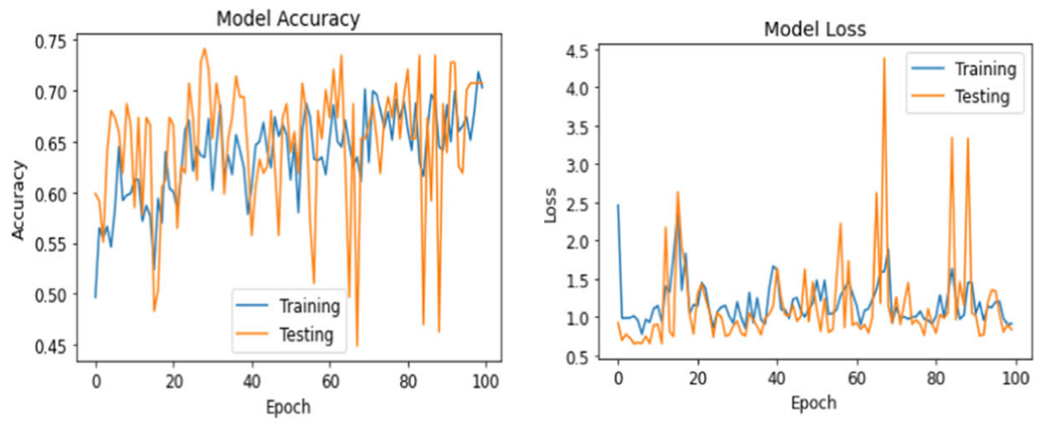


**Fig 7. Fine -Tuned ResNet50 Models Performance Graph**

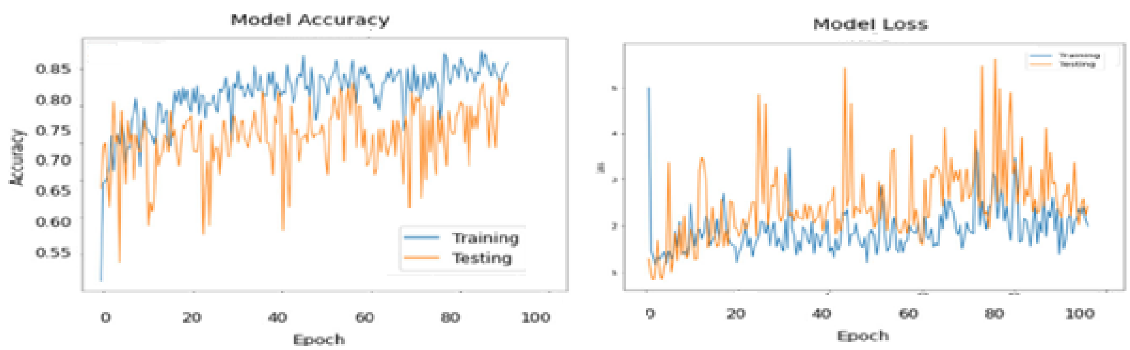


**Fig 8. Fine-Tuned InceptionV3 Models Performance Graph**

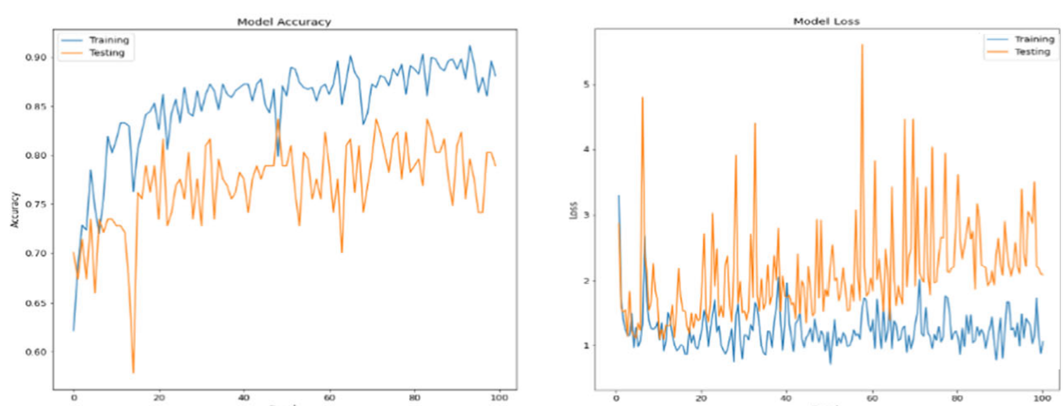


**Fig 9. Fine-Tuned Xception Models Performance Graph**

## 4 Discussion

Individuals can be diagnosed for COVID-19 using CT scan images. It provides a thorough view of the specific location, allowing us to identify internal flaws, damage, the size of the sections, tumors, There are not many changes between imaging and medical examination; nonetheless, there are some significant variances between the processes being used. Unlike imaging testing, where there are no lengthy processes to adhere to, clinical examination forms are often highly irritating to file during the critical situation. Naturally, clinical testing has a little bit more reliability since physicians individually review its results; in image testing, however, a machine performs this task; its intelligence is merely clever until it receives commands. With present method, the CT scan photos are categorized as either positive or negative. The proposed system examined four deep learning methods, including N-VGG19, ResNet50, InceptionV3, and Xception, in order to confirm that the suggested approach is credible. as it assists us to understand the benefits and drawbacks of each method. The N-VGG-19 takes just 12.89 ms to forecast the results, while the Xception and InceptionV3 models require 13.53 ms and 17.49 ms, respectively. The outcomes show that, when examining each modality independently, the N-VGG19 model performs better than all of the constructed versions of the algorithms for the CT image detector. The suggested method adopted a well-organized strategy that clinicians may employ for large patient monitoring. It will generate results more quickly and with more precision than the existing RT-PCR approach. This model may be expanded to categorize CT scan pictures infected for coronavirus according to the intensity of COVID-19 dissemination in the lung region.

## 5 Conclusion

The present work designed and evaluated a binary-classification deep learning methodology for detection of infection in the chest with the help of CT images. The suggested method have given a comprehensive evaluation of numerous previously trained neural network modules, including ResNet50, InceptionV3, N-VGG19, and Xception, using the Adamax optimizer and data augmentation technique. The N-VGG-19 performed better than all other deep learning models, with an accuracy of 90% when compared. To properly evaluate the potential of the suggested method, additional investigation and evaluation on bigger and more diversified databases are required.

## References


1) Agaoglu JNB, Yildiz J, Dogan OA, Kose G, Demirkol YK, Irvem A, et al. Yasemin Kendir Demirkol, Arzu Irvem, Levent Doganay, and Gizem Dinler Doganay. *J Virol Methods, 2022 Available*. Available from: https://doi.org/10.1016/j.jviromet.2021.114404.
2) Sun H, Wang A, Wang L, Wang B, Tian G, Yang J, et al. Systematic tracing of susceptible animals to SARS-CoV-2 by a bioinformatics framework. *Front Microbiol*. 2022. Available from: https://doi.org/10.3389/fmicb.2022.781770.
3) Wang D, Hu B, Hu C, Zhu F, Liu X, Zhang X, et al. Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus-infected pneumonia in Wuhan, China. *JAMA*. 2020;323:1061–1069. Available from: https://doi.org/10.1001/jama.2020.1585.
4) Pu R, Liu S, Ren X, Shi D, Ba Y, Huo Y, et al. The screening value of RT-LAMP and RT-PCR in the diagnosis of COVID-19: systematic review and meta-analysis. *J Virol Methods*. 2022;300. Available from: https://doi.org/10.1016/j.jviromet.2021.114392.
5) Lee Y, Kim YS. The application of a deep learning system developed to reduce the time for RT-PCR in COVID-19 detection. *Sci Rep*. 2022;12:1–10. Available from: https://doi.org/10.1038/s41598-022-05069-2.
6) Fields BKK, Demirjian NL, Dadgar H, Gholamrezanezhad A. Imaging of COVID-19: CT, MRI, and PET. *Semin Nucl Med*. 2021;p. 312–320. Available from: https://doi.org/10.1053/j.semnuclmed.2020.11.003.
7) Roberts M, Driggs D, Thorpe M, Gilbey J, Yeung M, Ursprung S, et al. Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans. *Nat Machine Intell*. 2021;3:199–217. Available from: https://doi.org/10.1038/s42256-021-00307-0.
8) Chung M. CT imaging features of 2019 novel coronavirus (2019-nCoV). *Radiology*. 2020;295:202–207. Available from: https://doi.org/10.1148/radiol.2020200230.
9) Menezes MCS, Santinelli DV, Pestana JC, Ferreira C, Carvalho MCRRD, Felix IO, et al. Distinct outcomes in COVID-19 patients with positive or negative RT-PCR test. *Viruses*. Available from: https://doi.org/10.3390/v14020175.
10) Zhao H, Deng X, Shao H, Jiang Y. COVID-19 diagnostic prediction on chest CT scan images using hybrid quantum-classical convolutional neural network". *J Biomol Struct Dyn*. 2024;42(7):3737–3746. Available from: https://doi.org/10.1080/07391102.2023.2226215.
11) Shorten C, Khoshgoftaar TM, Furht B. Deep learning applications for COVID-19. *J Big Data*. 2021;p. 1–54. Available from: https://doi.org/10.1186/s40537-020-00392-9.
12) Afshar P, Rafiee MJ, Naderkhani F, Heidarian S, Enshaei N, Oikonomou A, et al. Human-level COVID-19 diagnosis from low-dose CT scans using a two-stage time-distributed capsule network. *Sci Rep*. 2022;12:1–11. Available from: https://doi.org/10.1038/s41598-022-08796-8.
13) Zheng C, Deng X, Fu Q, Zhou Q, Feng J, Ma H, et al. Deep learning-based detection for COVID-19 from chest CT using weak label. *Medrxiv*. 2020. Available from: https://doi.org/10.1101/2020.03.12.20027185.
14) Mukherjee H, Ghosh S, Dhar A, Obaidullah SM, Santosh KC, Roy K. Deep neural network to detect COVID-19: one architecture for both CT Scans and Chest X-rays. *Applied Intelligence*. 2020;44:2777–2789. Available from: https://doi.org/10.1007/s10489-020-01943-6.
15) Stephen O, Sain M, Maduh UJ, Jeong DU. An efficient deep learning approach to pneumonia classification in healthcare. *Journal of Healthcare Engineering*. 2019. Available from: https://doi.org/10.1155/2019/4180949.

16) Chouhan V, Singh SK, Khamparia A, Gupta D, Tiwari P, Moreira C, et al. A novel transfer learning based approach for pneumonia detection in chest X-ray images. *Applied Sciences*. 2020;10(2). Available from: https://doi.org/10.3390/app10020559.
17) Lahsaini I, Daho MEH, Chikh MA. Deep transfer learning based classification model for covid-19 using chest CT-scans". *Pattern Recognition Lett*. 2021;152:122–130. Available from: https://doi.org/10.1016/j.patrec.2021.08.035.
18) Kaur T, Gandhi TK. Classifier Fusion for Detection of COVID-19 from CT Scans. *Circuits, Systems, and Signal Processing*. 2022;41(6):3397–3414. Available from: https://dx.doi.org/10.1007/s00034-021-01939-8.
19) Toğaçar M, Ergen B, Cömert Z. COVID-19 detection using deep learning models to exploit Social Mimic Optimization and structured chest X-ray images using fuzzy color and stacking approaches. *Computers in Biology and Medicine*. 2020;121:103805–103805. Available from: https://dx.doi.org/10.1016/j.compbiomed.2020.103805.
20) Zahangir AM, Rahman MM. Covid_mtnet: Covid-19 detection with multi-task deep learning approaches. *Electrical Engineering and System ScienceAvailable from*. 2020. Available from: http://arxiv.org/abs/2004.03747.
21) Zhao W, Zhong Z, Xie X, Yu Q, Liu J. Relation between chest CT findings and clinical conditions of coronavirus disease(covid-19) pneumonia: a multicenter study. *Am J Roentgenol*. 2020;214(5):107–107. Available from: https://doi.org/10.2214/ajr.20.22976.
22) Wang S, Kang B, Ma J, Zeng X, Xiao M, Guo J, et al. A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19). *MedRxiv, 2020b Available from*. Available from: https://doi.org/10.1101/2020.02.14.20023028.
23) Rahman MM, Walid MDAA, Galib SMS, Azad MM, Rahman W, Shafi ASM, et al. Covid-19 detectionfrom chest CT images using optimized deep features and ensemble classification. *system and Soft Computing*. 2024;6. Available from: https://doi.org/10.1016/j.sasc.2024.200077.
24) Appavu NK, Babu CNK, Kadry S. COVID-19 classification in X-ray/CT images using pretrained deep learning schemes. *Multimedia Tools and Applications*. 2024. Available from: https://dx.doi.org/10.1007/s11042-024-18721-y.
25) Hsu CC, Lee CM, Chiang YF, Chou YS, Jiang CY, Tai SC, et al. Simple 2D Convolutional Neural Network-based Approach for COVID-19 Detection . *Electrical Engineering and System Science*. 2024. Available from: https://doi.org/10.48550/arXiv.2403.11230.
26) Zolya MA, Baltag C, VBratu D, Coman S, Moraru SA. COVID-19 Detection and Diagnosis Model on CT Scans Based on AI Techniques. *Bioengineering*. 2024;11(1):79–79. Available from: https://dx.doi.org/10.3390/bioengineering11010079.