# <u>Automatic Detection of COVID-19 in Chest X-ray Images Using Deep Convolutional Neural Networks</u>

**Integrated M.Tech. 4th Semester (IIT Dhanbad student)**

**Integrated Master of Technology**

*in*

*Mathematics and Computing*

*BY*


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*UNDER THE SUPERVISION OF*

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**INDIAN INSTITUTE OF INFORMATION TECHNOLOGY, ALLAHABAD**

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# CANDIDATE’S DECLARATION

We hereby certify that the work which is being presented in the B.Tech. Mini-Project Report entitled “**Automatic Detection of COVID-19 in Chest X-ray Images Using Deep Convolutional Neural Networks”** being submitted as a part of Mid Semester Project Evaluation to the Department of Information Technology of Indian Institute Of Information Technology, Allahabad, is an authenticated record of our original work under the guidance and supervision of Prof. U.S. Tiwary from May 2020 to July 2020.We have adequately cited and referenced the original sources and have adhered to all principles of academic honesty and integrity.

Date:
Place: IIIT Allahabad

Signature:

Krishna Pal Deora
SRIP_2020_R21

## CERTIFICATE FROM SUPERVISOR

This is to certify that the statement made by the candidate is correct to the best of my knowledge and belief. The project entitled "**Automatic Detection of COVID-19 in Chest X-ray Images Using Deep Convolutional Neural Networks"** is a record of candidates' work carried out by them under my guidance and supervision. I do hereby recommend that it should be accepted in the fulfilment of the requirements of the mini project at IIIT Allahabad.

Prof. U.S. Tiwary,
IIIT-Allahabad

**ACKNOWLEDGEMENT**

I would like to acknowledge and extend our heartfelt gratitude to Prof. U.S. Tiwary, Indian Institute of Information Technology Allahabad, who guided me through this project. His keen vital encouragement, superb guidance, and constant support are the motive force behind this project work. I would like to show my warm thanks to all my friends for their continuous motivation and encouragement during this project. I am very thankful to all the technical and non-technical staffs of the college for their assistance and cooperation.

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SRIP_2020_R21

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# 1. Introduction

The 2019 novel coronavirus (COVID-19) pandemic appeared in Wuhan, China in December 2019 and has become a serious public health problem worldwide . The virus that caused COVID-19 pandemic disease was called as severe acute respiratory syndrome coronavirus 2, also named SARS-CoV-2 . Coronaviruses (CoV) are a large family of viruses that cause diseases resulting from colds such as the Middle East Respiratory Syndrome (MERS-CoV) and Severe Acute Respiratory Syndrome (SARS-CoV).

Coronavirus disease (COVID-19) is a new species that was discovered in 2019 and has not been previously identified in humans. Coronaviruses are zoonotic due to contamination from animals to humans.

There are studies that the SARS-CoV virus is contaminated from musk cats to humans, and the MERS-CoV virus is contaminated from dromedary to humans . COVID-19 virus is presumed to be contaminated from bats to humans . Respiratory transmission of the disease from person to person caused rapid spread of the epidemic. While COVID-19 causes milder symptoms in about 82 percent of cases, the others are severe or critical . Coronavirus cases total number is approximately 335,403 and 14,611 of them died and 97,636 were recovered. Currently infected patients' number is 223,156. While 95% of the number of infected patients survive the disease slightly, 5% the rest has a serious or critical condition . Signs of infection include respiratory symptoms, fever, cough and dyspnea. In more serious cases, the infection can cause pneumonia, severe acute respiratory syndrome, septic shock, multi-organ failure, and death. It has been determined that men are more infected than women and that there is no death in children between the ages of 0-9 . Respiratory rates of cases with COVID-19 pneumonia have been shown to be faster compared to healthy people.

## 2. Motivation

The 2019 novel coronavirus (COVID-19), with a starting point in China, has spread rapidly among people living in other countries, and is approaching approximately 305,275 cases worldwide according to the statistics of European Centre for Disease Prevention and Control. There are a limited number of COVID-19 test kits available in hospitals due to the increasing cases daily. Therefore, it is necessary to implement an automatic detection system as a quick alternative diagnosis option to prevent COVID-19 spreading among people. In this study, three different convolutional neural network based models (ResNet50, InceptionV3 and InceptionResNetV2) have been proposed for the detection of coronavirus pneumonia infected patient using chest X-ray radiographs. ROC analyses and confusion matrices by these three models are given and analyzed using 5-fold cross validation. Considering the performance results obtained, it is seen that the pre-trained ResNet50 model provides the highest classification performance with 98% accuracy among other two proposed models (97% accuracy for InceptionV3 and 87% accuracy for Inception-ResNetV2).

## 3. Problem Definition & Objective

The problem is to classify the chest X-ray images into three categories namely- Covid-19 infected, Pneumonia infected or Normal (Healthy) chest x-ray image.

## 4. Literature Survey

Recently, researchers have perceived the imaging patterns on chest CT for detecting the COVID-19 in chest CT . Fang et al. studied the sensitivity of RT-PCR and chest CT during the detection of COVID-19. They analyzed the travel history and symptoms of 2 patients and found that the sensitivity of chest CT for detection of COVID-19 is much higher than RT-PCR. Xie et al. also reported that the 3% of 167 patients had negative RT-PCR for COVID-19 detection. However, chest CT has better sensitivity of detection of COVID-19 over RT-PCR. Berheim et al. studied 121 infected patients' chest CT from four different centers of China. The relationship between CT scan and symptom onset is established. They found that the severity of disease increased with time from onset of symptoms and designated the signs of disease. Recently, deep learning techniques have been widely used in detection of acute pneumonia in chest CT images . Li et al. developed a deep learning model named as COVNet to extract visual features from chest CT for detection of COVID-19. They used visual features to distinguish between community acquired pneumonia and other nonpneumonia lung diseases. However, COVNet is unable to categorize the severity of this disease. Gozes et al. developed an artificial intelligence-based CT analysis tool for detecting and quantification of COVID-19. The system extracted slice of opacities in the lungs automatically. The developed system achieved 98.2% sensitivity and 92.2% specificity. The output of system provides quantitative opacity measure and 3D volume display for opacities. The system is robust against pixel spacing and slice thickness .Shan et al. developed a deep learning-based system named VB-net for automatic segmentation of all the lung and infection sites using chest CT. Xu et al. developed a prediction model to discriminate COVID-19 pneumonia and influenza-A viral pneumonia using deep learning techniques. The CNN model was used for prediction. The maximum accuracy obtained from prediction model was 86.7%. Wang et al. investigated the radiographic changes in CT images of infected patients. They developed a deep learning-based prediction model that utilizes the modified inception transfer learning technique. The features are extracted from CT images for prior diagnosis. The accuracy of 89.5% obtained from this method is better than Xu's model and saved time for diagnosis. Narin et al. proposed an automatic deep convolution neural network– based transfer models for prediction of COVID-19 in chest Xray images. They used InceptionV3, Inception-ResNetV2, and ResNet50 models for better prediction. The ResNet50 pre-trained model produced accuracy of 98%, which is higher than . Sethy et al. developed a deep learning model for detecting COVID-19 from X-ray images. They extracted deep features and transferred them to support vector machine for classification. The accuracy of 95.38% obtained from the proposed model, which is better than. From the extensive review, it has been found that the chest CT images can be used for early classification of COVID-19- infected patients .Therefore, in this paper, computational models are used to classify COVID-19 patients from chest CT images.

## 5. Materials and Methods

### 5.1 Dataset

In this study, chest X-ray images of 50 COVID-19 patients have been obtained from the open source GitHub repository shared by Dr. Joseph Cohen. This repository is consisting chest X-ray / CT images of mainly patients with acute respiratory distress syndrome (ARDS), COVID-19, Middle East respiratory syndrome (MERS), pneumonia, severe acute respiratory syndrome (SARS). In addition, 50 normal chest X-ray images were selected from Kaggle repository called "Chest X-Ray Images (Pneumonia)" . Our experiments have been based on a created dataset with chest X-ray images of 50 normal and 50 COVID-19 patients (100 images in total). All images in this dataset were resized to 224x224 pixel size. In Figure 2 and Figure 3, representative chest X-ray images of normal and COVID-19 patients are given, respectively.

**CoronaHack-Chest X-Ray Dataset:**[https://www.kaggle.com/praveengovi/coronahack-chest-xraydataset?](https://www.kaggle.com/praveengovi/coronahack-chest-xraydataset?)

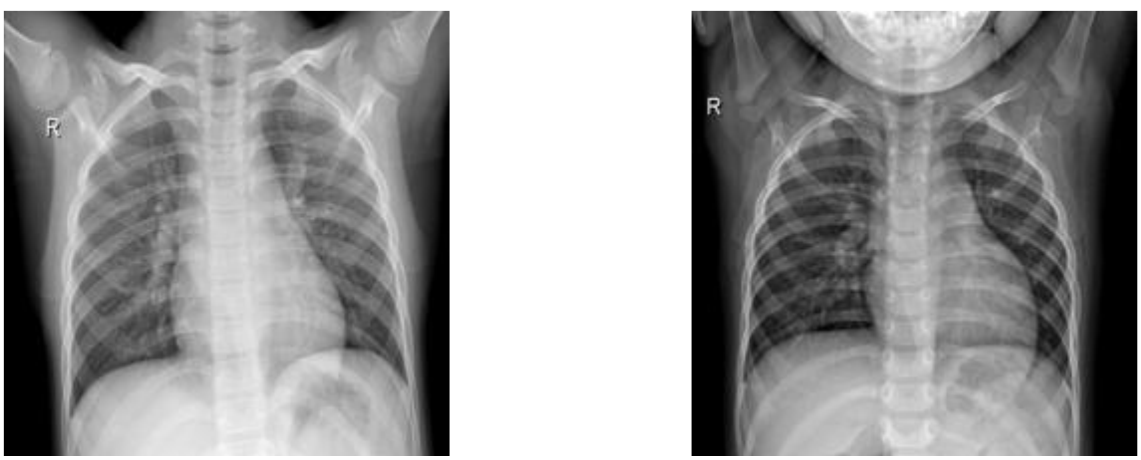


**Figure 2.** Representative chest X-ray images of normal

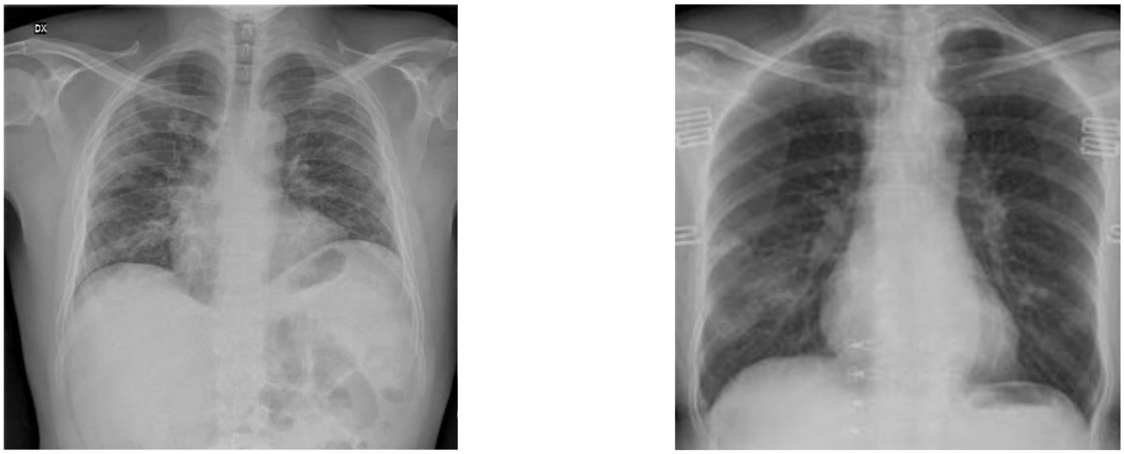

**Figure 3.** Representative chest X-ray images of COVID-19 patients.

### 5.2 Deep Transfer Learning

Deep learning is a sub-branch of the machine learning field, inspired by the structure of the brain. Deep learning techniques used in recent years continue to show an impressive performance in the field of medical image processing, as in many fields. By applying deep learning techniques to medical data, it is tried to draw meaningful results from medical data.

Deep learning models have been used successfully in many areas such as classification, segmentation and lesion detection of medical data. Analysis of image and signal data obtained with medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and X-ray with the help of deep learning models. As a result of these analyzes, detection and diagnosis of diseases such as diabetes mellitus, brain tumor, skin cancer and breast cancer are provided with convenience.

In the analysis of medical data, one of the biggest difficulties faced by researchers is the limited number of available datasets. Deep learning models often need a lot of data. Labeling this data by experts is both costly and time consuming. The biggest advantage of using transfer learning method is that it allows the training of data with fewer datasets and requires less calculation costs. With the transfer learning method, which is widely used in the field of deep learning, the information gained by the pre-trained model on a large dataset is transferred to the model to be trained.

In this study, we built deep convolutional neural network (CNN) based ResNet50, InceptionV3 and Inception-ResNetV2 models for the classification of COVID-19 Chest X-ray images to normal and COVID-19 classes. In addition, we applied transfer learning technique that was realized by using ImageNet data to overcome the insufficient data and training time. The schematic representation of conventional CNN including pre-trained ResNet50, InceptionV3 and Inception ResNetV2 models for the prediction of COVID-19 patients and normal were depicted in Figure 4.

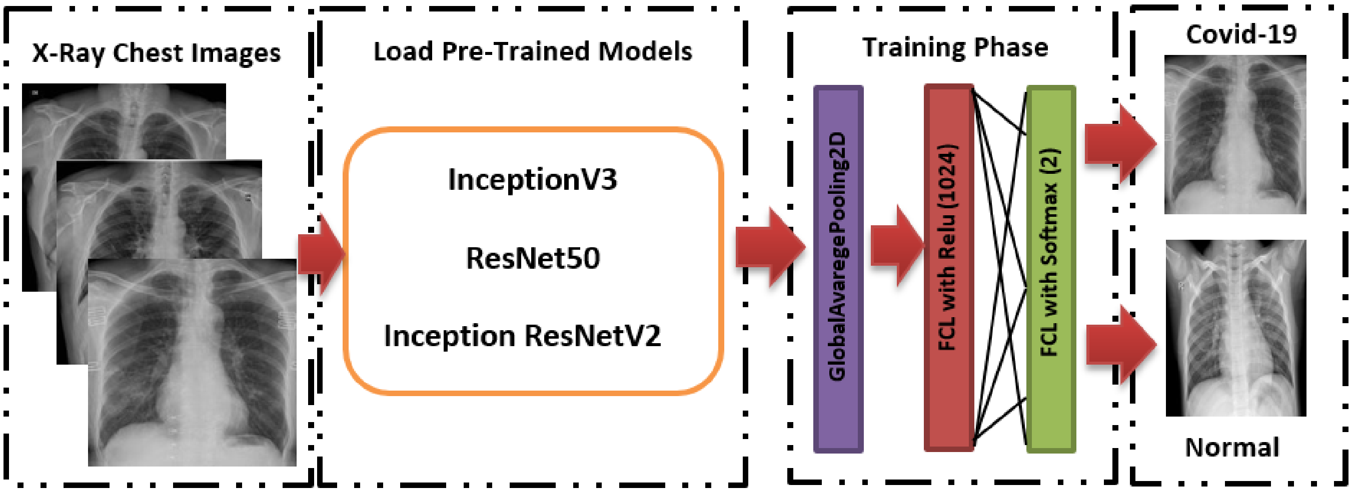


**Figure 4.** Schematic representation of pre-trained models for the prediction of COVID-19 patients and normal

Residual neural network (ResNet) model is an improved version of convolutional neural network (CNN). ResNet adds shortcuts between layers to solve a problem. Thanks to this, it prevents the distortion that occurs as the network gets deeper and more complex. In addition, bottleneck blocks are used to make training faster in the ResNet model. ResNet50 is a 50-layer network trained on the ImageNet dataset. ImageNet is an image database with more than 14 million images belonging to more than 20 thousand categories created for image recognition competitions. InceptionV3 is a kind of convolutional neural network model. It consists of numerous convolution and maximum pooling steps. In the last stage, it contains a fully connected neural network. As with the ResNet50 model, the network is trained with ImageNet dataset. The model consists of a deep convolutional network using the Inception ResNetV2 architecture that was trained on the ImageNet-2012 dataset. The input to the model is a 299×299 image, and the output is a list of estimated class probabilities.

### 5.3 Experimental Setup

Python programming language was used to train the proposed deep transfer learning models. All experiments were performed on a Google Colaboratory Linux server with Ubuntu 16.04 operating system using Tesla K80 GPU graphics card. CNN models (ResNet50, InceptionV3 and Inception-ResNetV2) were pre-trained with random initialization weights using the Adam optimizer. The batch size, learning rate and number of epochs were experimentally set to 2, 1e-5 and 30, respectively for all experiments. The dataset used was randomly split into two independent datasets with 80% and 20% for training and testing respectively. As cross validation method, k-fold was chosen and results were obtained according to 5 different k values (k=1-5) as shown in Figure 5.

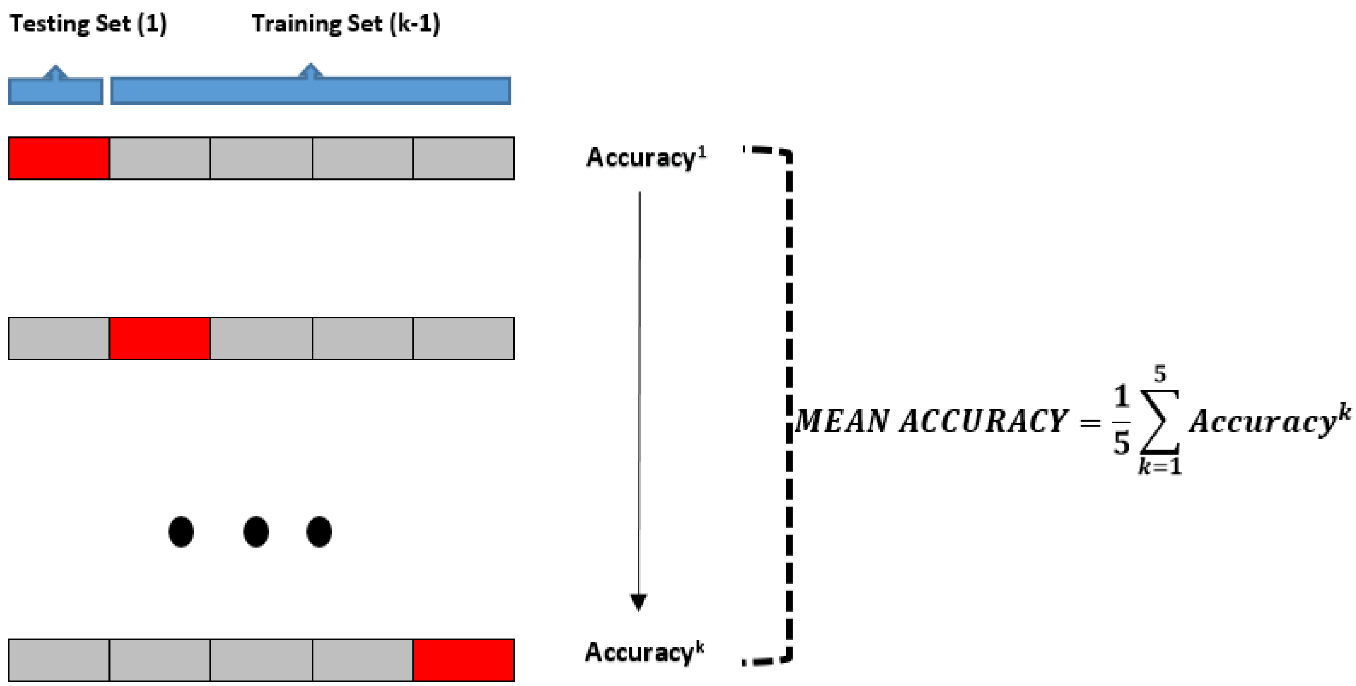


**Figure 5.** Visual display of testing and training datasets for 5-fold cross validation.

## 5.4 Performance Metrics

5 criteria were used for the performances of deep transfer learning models. These are:

Accuracy = (TN + TP) / (TN + TP + FN + FP) (1)

Recall = TP / (TP + FN) (2)

Specificity = TN / (TN + FP) (3)

Precision = TP / (TP + FP) (4)

F1-Score = 2x((PrecisionxRecall)/(Precision+Recall)) (5)

TP, FP, TN and FN given in Equation (1) – (5) represent the number of True Positive, False Positive, True Negative and False Negative, respectively. Given a test dataset and model, TP is the proportion of positive (COVID-19) that are correctly labeled as COVID-19 by the model; FP is the proportion of negative (normal) that are mislabeled as positive (COVID-19); TN is the proportion of negative (normal) that are correctly labeled as normal and FN is the proportion of positive (COVID-19) that are mislabeled as negative (normal) by the model.

## 6.Pre-Requisites:

### 6.1 Hardware:

- NVIDIA-Quadro K[6000] Graphics Driver
- GPU enable system with at-least 8 GB internal memory
- Intel core i7 processor
- CUDA installed system

### 6.2 Software:

- **Language Used:** Python 3.0
- **Tools Used:** Anaconda 3.0
- **Libraries Used:** Chainer, numpy, cupy, cuda,OpenCV
- **Dataset Used:** CoronaHack-Chest X-Ray Dataset(Kaggle)

## 7. Results and Discussion

In this study, chest X-ray images have been used for the prediction of coronavirus disease patients (COVID-19). Popular pre-trained models such as ResNet50, InceptionV3 and Inception ResNetV2 have been trained and tested on chest X-ray images. Training accuracy and loss values for fold-3 of the pre-trained models are given in Figure 6 and Figure 7, respectively. The training stage has been carried out up to 30th epoch to avoid overfitting for all pre-trained models. It can be seen from Figure 6 that the highest training accuracy is obtained with the ResNet50 model. InceptionV3 and Inception-ResNetV2 models have similar performance. However, it is seen that ResNet50 shows a fast training process than other models. Although the pre-trained models give very high initial values, the initial values are below 70% due to the low number of data. The training loss values of ResNet50, InceptionV3 and Inception ResNetV2 are shown in Figure 7. When the loss figure are analyzed, it is seen that the loss values decrease in three pre-trained models during the training stage. It can be said that the ResNet 50 model both decreases loss values faster and approaches zero.

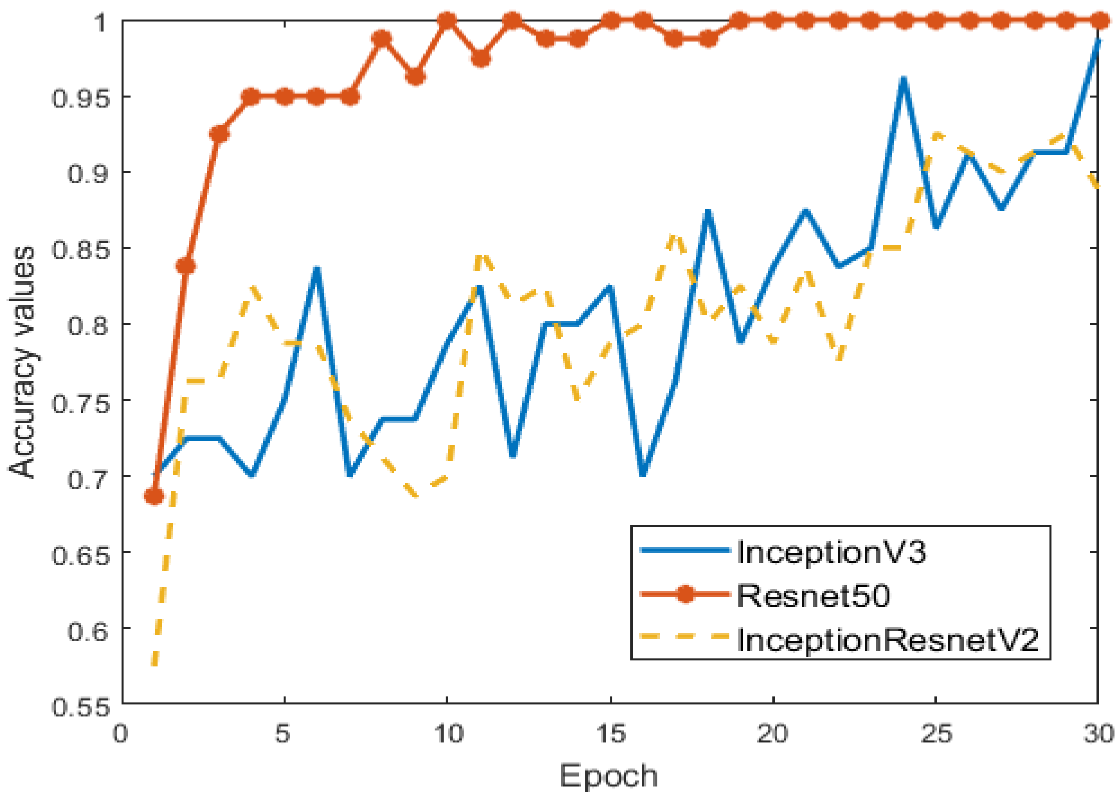


**Figure 6.** The performance of three pre-trained models (Training accuracy for fold-3)

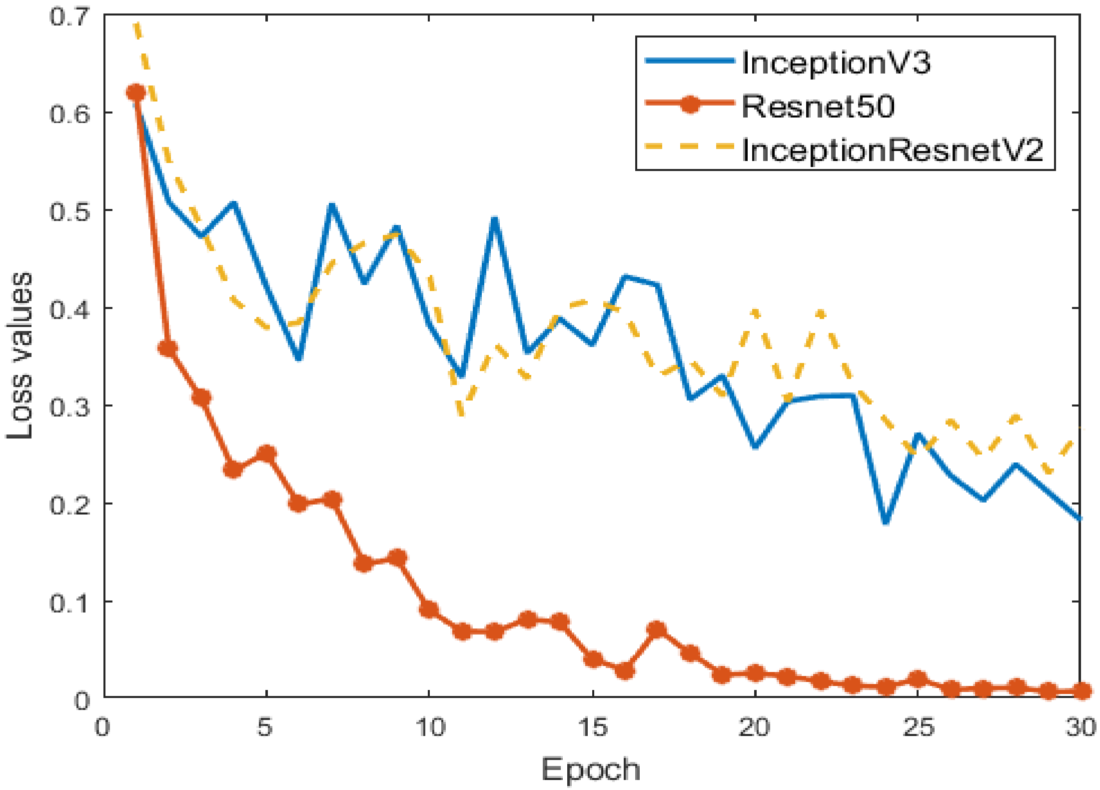


**Figure 7.** The performance of three pre-trained models (Training loss values for fold-3)

In Figure 8, confusion matrices of COVID-19 and normal test results of the models are given. Firstly, InceptionV3 pre-trained model classified 10 of the COVID-19 as True Positive for fold-3 and classified 10 of the normal as True Negative. Secondly, ResNet50 model also classified 10 of the COVID-19 as True Positive for fold-3 and classified 10 of the normal as True Negative. Lastly, Inception ResNetV2 classified 10 of the COVID-19 as True Positive for fold-3 and classified 9 of the normal as True Negative. Besides the confusion matrix, receiver operating characteristic curve (ROC) plots and areas for each model are given. InceptionV3 and ResNet50 pre-trained models appear to be very high.

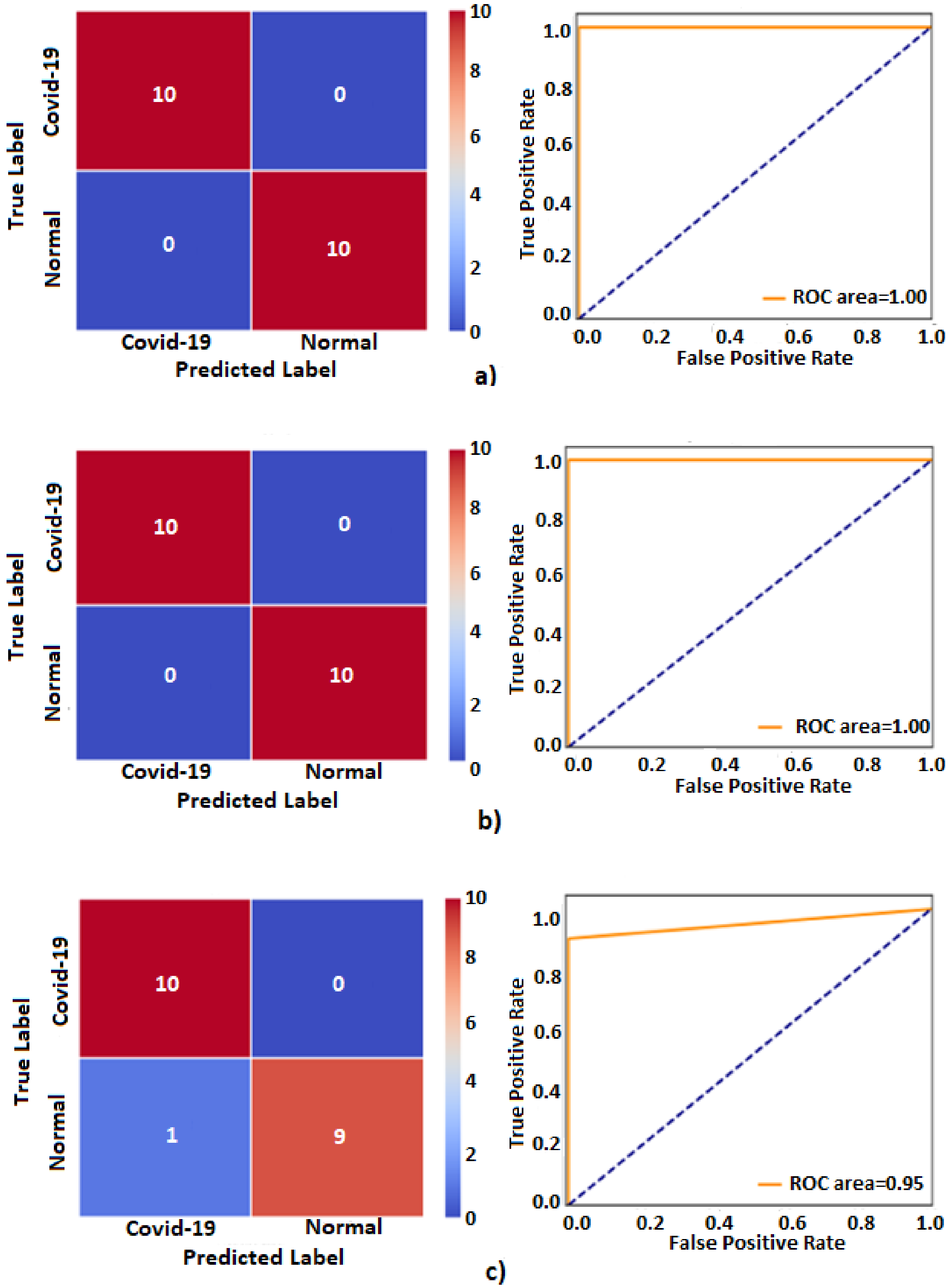


**Figure 8.** The confusion matrix and ROC plots obtained using pre-trained models for fold-3 results: a) InceptionV3, b) ResNet50, c) Inception-ResNetV2.

In another detailed performance, comparisons of three models using the test data are shown in Table 1. We have obtained the best performance as an accuracy of 98%, recall of 96%, and specificity value of 100% for ResNet50 pre-trained model. The lowest performance values have been yielded an accuracy of 87%, recall of 84%, and specificity value of 90% for Inception-ResNetV2. As a result, the ResNet50 model provides superiority over the other two models both training and testing stage. **Table 1.** Prediction performance results obtained from different pre-trained CNN models for 5-fold cross validation methods. The abbreviations in Table 1 are: True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), Accuracy (Acc), Recall (Rec), Specificity (Spe), Precision (Pre), F1-Score (F1).

| MODELS/FOLD | | Confusion matrix and Performance results (%) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | TP | TN | FP | FN | Acc | Rec | Spe | Pre | F1 |
| InceptionV3 | Fold-1 | 7 | 10 | 0 | 3 | 85 | 70 | 100 | 100 | 82 |
| | Fold-2 | 10 | 10 | 0 | 0 | 100 | 100 | 100 | 100 | 100 |
| | Fold-3 | 10 | 10 | 0 | 0 | 100 | 100 | 100 | 100 | 100 |
| | Fold-4 | 10 | 10 | 0 | 0 | 100 | 100 | 100 | 100 | 100 |
| | Fold-5 | 10 | 10 | 0 | 0 | 100 | 100 | 100 | 100 | 100 |
| | Mean | | | | | 97 | 94 | 100 | 100 | 96 |
| ResNet50 | Fold-1 | 8 | 10 | 0 | 2 | 90 | 80 | 100 | 100 | 89 |
| | Fold-2 | 10 | 10 | 0 | 0 | 100 | 100 | 100 | 100 | 100 |
| | Fold-3 | 10 | 10 | 0 | 0 | 100 | 100 | 100 | 100 | 100 |
| | Fold-4 | 10 | 10 | 0 | 0 | 100 | 100 | 100 | 100 | 100 |
| | Fold-5 | 10 | 10 | 0 | 0 | 100 | 100 | 100 | 100 | 100 |
| | Mean | | | | | 98 | 96 | 100 | 100 | 98 |
| Inception-ResNetV2 | Fold-1 | 9 | 7 | 3 | 1 | 80 | 90 | 70 | 75 | 82 |
| | Fold-2 | 10 | 9 | 1 | 0 | 95 | 100 | 90 | 91 | 95 |
| | Fold-3 | 10 | 9 | 1 | 0 | 95 | 100 | 90 | 91 | 95 |
| | Fold-4 | 7 | 10 | 0 | 3 | 85 | 70 | 100 | 100 | 82 |
| | Fold-5 | 6 | 10 | 0 | 4 | 80 | 60 | 100 | 100 | 75 |
| | Mean | | | | | 87 | 84 | 90 | 91 | 86 |

There are very few studies on literature due to the emergence of COVID-19 virus disease. Some of these are as follows: Prabira et al. proposed a detection of COVID-19 using X-ray images based on deep feature and SVM. They collected X-ray images from GitHub, Kaggle and Open-I repository. They extracted the deep feature of CNN models and fed to SVM classifier individually. They have obtained 95.38% of accuracy for ResNet50&SVM. Fei et al., tried to predict COVID-19 patients using "VB-Net" neural network to segment COVID-19 infection regions in CT scans. They handled the results statistically. They obtained dice similarity coefficients of 91.6%±10.0%. Xiaowei et al. , proposed an early prediction model to classification COVID-19 pneumonia from Influenza-A viral pneumonia and healthy cases using pulmonary CT images using deep learning techniques. Their CNN model has yielded the highest overall accuracy was 86.7 % CT images. Shuai et al. , used CT images to predict COVID-19 cases. They also used the Inception transfer-learning model to establish the algorithm. They obtained an accuracy of 89.5% with specificity of 88.0% and sensitivity of 87.0%.
In addition to these studies in the literature, the main advantages of our study can be summarized as follows:

**(I)** Chest X-ray images have been used in the study. X-ray images can be obtained from any hospital very easily, quickly and without difficulty.

**(II)** Our method is a completely end-to-end system. So, it does not have any feature extraction or selection.

**(III)** Three different pre-trained common models are compared such as ResNet50, InceptionV3 and Inception-ResNetV2.

**(IV)** Although it is a very new subject and the number of data is limited, the results are quite high.

The main problem of our study is the limited number of COVID-19 X-ray images used for the training of deep learning models. In order to overwhelm this problem, we have used deep transfer learning models. If we reach more data in the coming days, we are planning to improve working with different models.

## 8. Conclusion

Early prediction of COVID-19 patients is vital to prevent the spread of the disease to other people. In this study, we proposed a deep transfer learning based approach using chest X-ray images obtained from COVID-19 patients and normal to predict COVID-19 patients automatically. Performance results show that the ResNet50 pre-trained model yielded the highest accuracy of 98% among the three models. In the light of our findings, it is believed that it will help doctors to make decisions in clinical practice due to the high performance. In order to detect COVID-19 at an early stage, this study gives insight on how deep transfer learning methods can be used. In subsequent studies, the classification performance of different CNN models can be tested by increasing the number of images in the dataset.

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## 10. Suggestions By Board Members