

# Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks

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## Abstract

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 12,245,417 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 Inception-ResNetV2) 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).

**Keywords:** Coronavirus; Pneumonia; Chest X-ray Radiographs; Convolutional Neural Network; Deep Transfer Learning

## 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 [1, 2]. The virus that caused COVID-19 pandemic disease was called as severe acute respiratory syndrome coronavirus 2, also named SARS-CoV-2 [3]. 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 [4]. 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 [4, 5]. COVID-19 virus is presumed to be contaminated from bats to humans [5]. 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 [6]. Coronavirus cases total number is approximately 12,420,705 and 558,091 of them died and 7,246,372 were recovered. Currently infected patients' number is 4,616,242. While 99% of the number of infected patients survive the disease slightly, 1% the rest has a serious or critical condition [7].

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 [4],[8]. 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 [6]. Respiratory rates of cases with COVID-19 pneumonia have been shown to be faster compared to healthy people [9].

Even in many developed countries, the health system has come to the point of collapse due to the increasing demand for intensive care units simultaneously. Intensive care units are filled with patients who get worse with COVID-19 pneumonia. The COVID-19 cases between the days of December 31th, 2019, and July 10th, 2020 is reported 12,245,417 confirmed cases all over the world [10].

According to the latest guidelines published by the Chinese government, the diagnosis of COVID-19 should be confirmed by gene sequencing for respiratory or blood samples as a key indicator for reverse transcription polymerase chain reaction (RT-PCR) or hospitalization. In

the current public health emergency, the low sensitivity of RT-PCR means that many COVID-19 patients will not be identified quickly and may not receive appropriate treatment. In addition, given the highly infectious nature of the virus, they run the risk of infecting a larger population [11].

Instead of the patients waiting to get positive virus tests, diagnoses now include everyone who reveals the prominent pneumonia pattern of chest scan COVID-19. Through this method, authorities will be able to isolate and treat patients more quickly. Even if death does not occur in COVID-19, some patients survive with permanent lung damage. According to the World Health Organization, COVID-19 also opens holes in the lungs like SARS, giving them a "honeycomb-like appearance" [6],[12].

Computed Tomography (CT) scan of the chest is one of the methods used to diagnose pneumonia. Artificial Intelligence (AI) based automated CT image analysis tools for the detection, quantification and monitoring of coronavirus and to distinguish patients with coronavirus from disease-free have been developed [13]. In a study by Fei et al., they developed a deep learning-based system for automatic segmentation of all lung and infection sites using chest CT [14]. Xiaowei et al. aimed to establish an early screening model to distinguish COVID-19 pneumonia and Influenza-A viral pneumonia from healthy cases using pulmonary CT images and deep learning techniques [15]. In Shuai et al. study, based on the COVID-19 radiographic changes from CT images, they have developed a deep learning method that can extract the graphical features of COVID-19 to provide clinical diagnosis prior to pathogenic testing and thus save critical time for the disease diagnosis [16].

MERS-CoV and SARS-CoV are expressed as cousins of COVID-19. There are scientific publications using chest X-ray images in the diagnosis of MERS-CoV and SARS-CoV. In the study of Ahmet Hamimi about MERS CoV showed that there are features in the chest X-ray and CT that are like the manifestations of pneumonia [17]. In the study by Xuanyang et al., data mining techniques were used to distinguish SARS and typical pneumonia based on X-ray images [18].

X-ray machines are used to scan the affected body such as fractures, bone dislocations, lung infections, pneumonia and tumors. CT scanning is a kind of advanced X-ray machine that examines the very soft structure of the active body part and clearer images of the inner soft tissues and organs [19]. Using X-ray is a faster, easier, cheaper and less harmful method than CT. Failure to promptly recognize and treat COVID-19 pneumonia may lead to increase in mortality.

In this study, we have proposed an automatic prediction of COVID-19 using a deep convolution neural network based pre-trained transfer models and Chest X-ray images. For this purpose, we have used ResNet50, InceptionV3 and Inception-ResNetV2 pre-trained models to obtain a higher prediction accuracy for small X-ray dataset. The novelty of this paper is summarized as follows: **i)** The proposed models have end-to-end structure without manual feature extraction and selection methods. **ii)** We show that ResNet50 is an effective pre-trained model among other two pre-trained models. **iii)** Chest X-ray images are the best tool for the detection of COVID-19. **iv)** The pre-trained models have been shown to yield very high results in the small dataset (50 COVID-19 vs. 50 Normal).

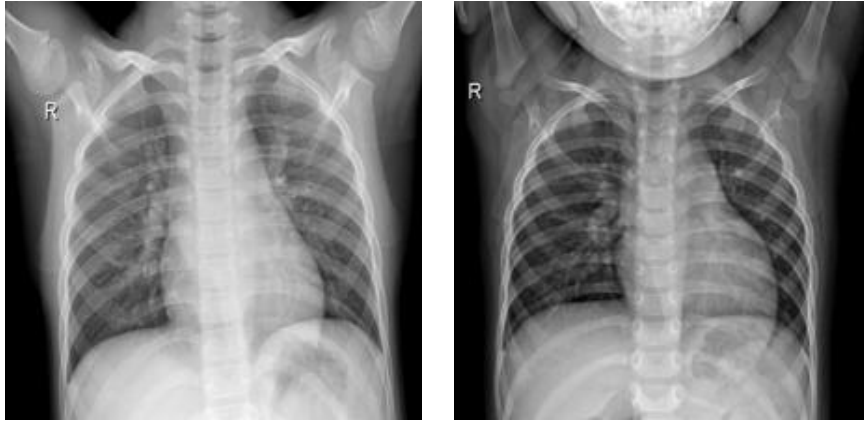
The manuscript is organized as follows: Dataset is expressed in detail in Section 2.1. Deep transfer learning models and experimental setup parameters are described in Section 2.2 and 2.3, respectively. Performance metrics are given in detail in Section 2.4. Discussion and obtained results from proposed models are presented in Section 3. Finally, in Section 4, the conclusion and the future works are summarized.

## **2. Materials and Methods**

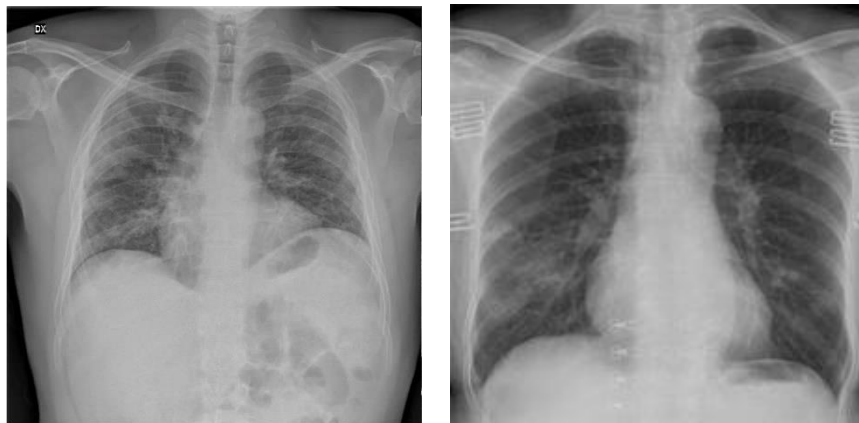
### **2.1 Dataset**

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 [20]. 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)” [21].

Our experiments have been based on a created dataset with chest X-ray images of 50 normal [21] and 50 COVID-19 patients [20] (100 images in total). All images in this dataset were resized to 224x224 pixel size. In Figure 1 and Figure 2, representative chest X-ray images of normal and COVID-19 patients are given, respectively.



**Figure 1.** Representative chest X-ray images of normal.



**Figure 2.** Representative chest X-ray images of COVID-19 patients.

## 2.2 Deep Transfer Learning

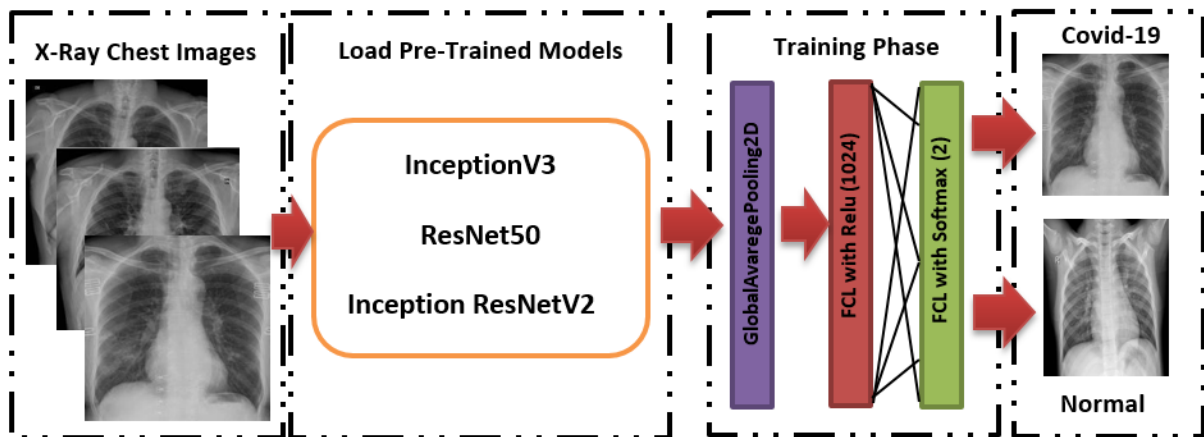
Deep learning is a sub-branch of the machine learning field, inspired by the structure of the brain. Deep learning techniques used in recent years continue to show an impressive performance in the field of medical image processing, as in many fields. By applying deep learning techniques to medical data, 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 [22-27].

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 3. It is also available publicly for open access at <https://github.com/drcerenkaya/COVID-19-Detection>.



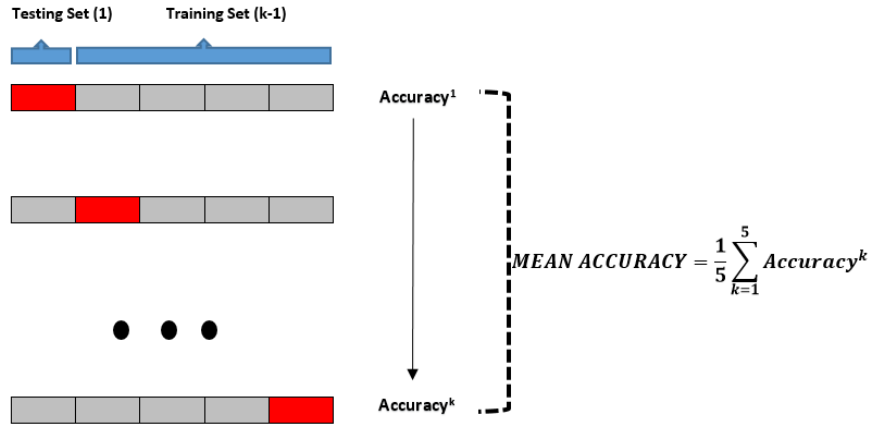
**Figure 3.** Schematic representation of pre-trained models for the prediction of COVID-19 patients and normal.

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 [28]. 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 [29]. 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 [30]. 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 [31].

## 2.3 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 4.



**Figure 4.** Visual display of testing and training datasets for 5-fold cross validation.

## 2.4 Performance Metrics

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

$$Accuracy = (TN + TP) / (TN + TP + FN + FP) \quad (1)$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) \quad (2)$$

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

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

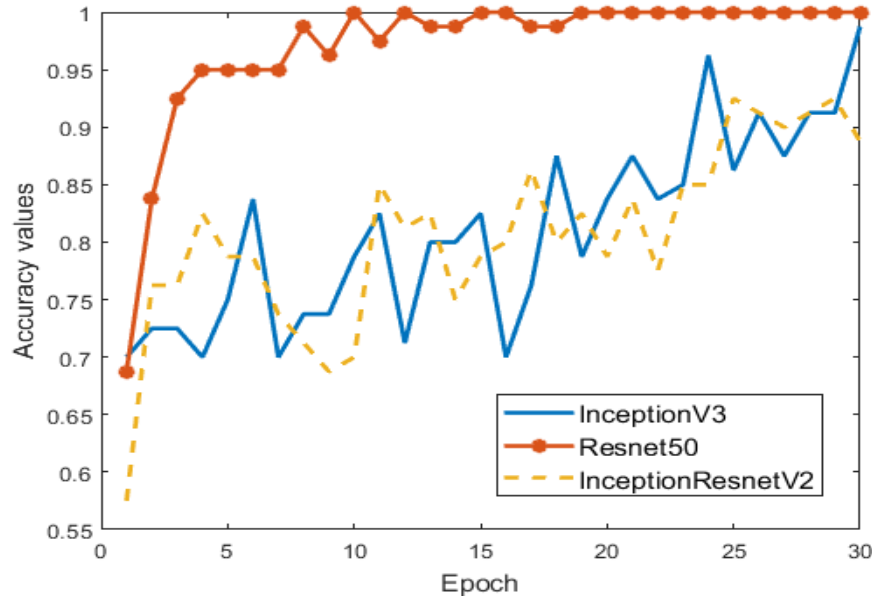
$$\text{F1-Score} = 2 \times ((\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})) \quad (5)$$

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.

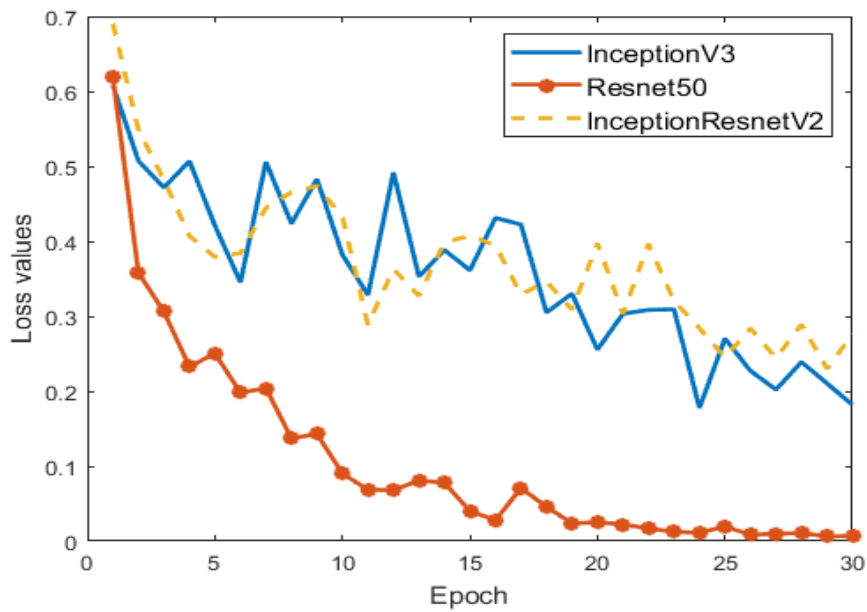
### 3. Results and Discussion

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 5 and Figure 6, 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 5 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 6. 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.





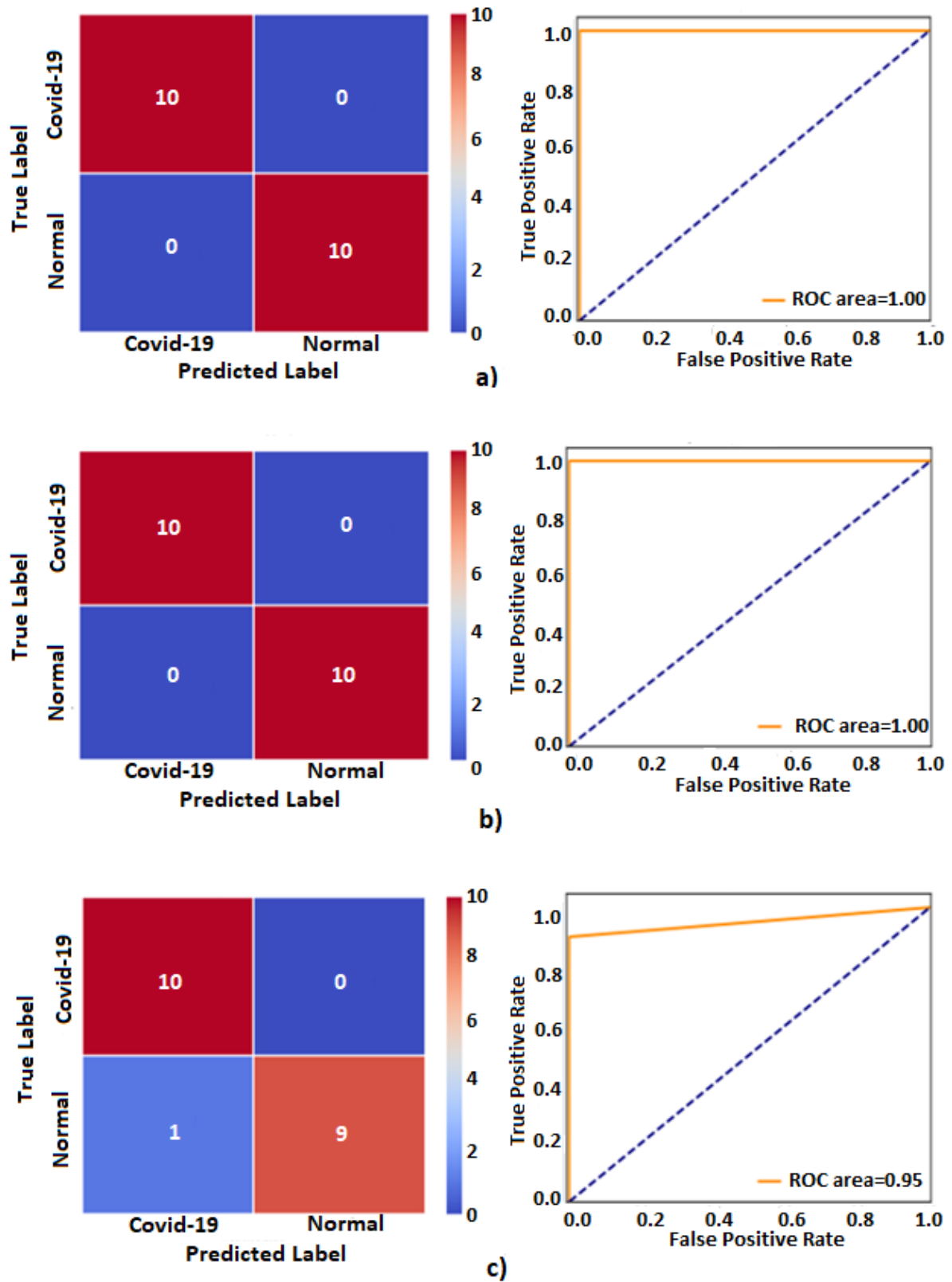
**Figure 5.** The performance of three pre-trained models (Training accuracy for fold-3)



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

In Figure 7, 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 7.** 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. [32] 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.

[14], 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  $91.6\% \pm 10.0\%$ . Xiaowei et al. [15], 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. [16], 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.

#### **4. 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.

### **Author contributions statement**

A.N. and C.K were involved in the study conception and acquisition of dataset. A.N conducted the experiments and analysed the results. A.N., C.K. and Z.P. wrote the manuscript and revised the draft critically. All authors reviewed the manuscript.

### **Competing interests**

The authors declare no competing interests.

### **Additional information**

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