Predicting pattern of coronavirus using X-ray and CT scan images

Payal Khurana Batra[1] · **Paras Aggarwal**[1] · **Dheeraj Wadhwa**[1] · **Mehul Gulati**[1]

Abstract

Novel coronavirus is a disease that can propagate easily with very minute carelessness and with very little physical contact between people. Presently, the world's central health institution called the World Health Organization has approved and advised the Reverse Transcription-Polymerase Chain Reaction (RT-PCR) swab test as the most important and effective diagnostic method to confirm if a patient has COVID-19 symptoms or not. This test takes at least a day for revealing the results, depending on the feasible resources in the neighborhood. Moreover, the RT-PCR test gives sometimes false positive results and slow in the process. To keep the potential virus carriers and potential causes of the disease quarantined as early as possible, there is still a requirement for a much faster and more accurate diagnostic process to supplement RT-PCR test of finding the patients affected by the virus. In this regard, radiological images such as X-ray and CT (Computerized Tomography) scan are found to be useful. The X-ray and CT scan have good screening modality; they are quick at capturing and finding and widely available around the world. Therefore, a deep learning model, which makes use of CT scan and X-ray images, has been proposed to automate and analyze the diagnostic process by utilizing Convolutional Neural Network (CNN). This model makes use of InceptionV3 deep learning model, a type of CNN. It is a lightweight deep learning model that is apt for mobile, laptop, and tablet platforms. The proposed model requires low memory space and gives an accuracy of about 96%, sensitivity of 93.48% for CXRs (Chest X-rays) and accuracy of 93%, sensitivity of 89.81 % for the CT scan images respectively. The proposed model is also compared with other deep learning models like VGG 16 (Visual Geometry Group), ResNet50V2 (Residual Network) and other existing deep learning models and it is found to be better in terms of accuracy and other performance parameters. Further, a web application has been developed from the proposed model. The web application is able to detect COVID-19 cases from the CT scan and X-ray images with significant accuracy.

Keywords Deep learning · Coronavirus · CT scan · X-ray · Prediction · Convolutional Neural Network (CNN)

1 Introduction

In December 2019, cases of unidentified pneumonia were reported in Wuhan, China (Wu et al. 2020; Huang et al. 2020). Since then, Coronavirus Disease 2019 has rapidly spread to all parts of the globe. This coronavirus disease is termed as COVID-19 and the virus named as SARS-CoV-2. The novel coronavirus has caused a pandemic resulting in over 235 million infected individuals, over 5 million deaths and this count is growing day by day (Who 2021). This invasive disease affects and kills our respiratory system (Kanne and Chest 2020). COVID-19 patient's symptoms match with the common flu, pneumonia, and other respiratory illnesses. These occur over a period of four to ten days from getting the infection. Acknowledged symptoms comprise fever, cough, shortness of breath, and chest tightness/pain (Singhal 2020). It may create confusion in the diagnosis of patients with COVID-19 and typical pneumonia. The patients who lost their lives due to COVID-19 were the usual victims of hypertension, diabetes, cerebral infarction, chronic bronchitis and coronary heart disease.

The World Health Organization (WHO) has approved the Reverse Transcription-Polymerase Chain Reaction (RT-PCR) swab test as a screening tool to diagnose COVID-19 cases (Corman et al. 2020). The sensitivity of RT-PCR depends on various factors such as the time span of symptoms, development of the virus, the speed of viral reproduction in the human respiratory system, time when the sample taken and quality of test procedure (Green et al.

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2020). Beside giving a false positive result, the process is slow and sometimes takes over a day to declare the result. Moreover, the result of the RT-PCR test is in terms of positive and negative only. It does not say about the severity of the disease. This gives rise to a requirement for a quick and accurate diagnostic test besides this existing method so that the growth of the virus can be restrained as soon as possible. As an alternative, no contact methods are useful to detect COVID-19.

Various diagnostic tools, such as lung ultrasound (LUS), Chest X-ray (CXR), and Computerized Tomography (CT) have been used to find variations in lungs related with COVID-19 (Araujo-Filho et al. 2020; Bernheim et al. 2020). Among various medical images, portable chest X-rays (CXRs) and CT scans are suggested as a good and feasible choice for COVID-19 detection. Although CT scan has been proved to be one of the most precise diagnostic methods for COVID-19, it has some important limitations such as around 70 times higher ionizing radiation than X-ray, high cost, and is not suitable for critically ill patients. Even though the cost per utility of the CT scan is high as compared to RT-PCR (Sriwijitalai and Wiwanitkit 2020), however, after the onset of symptoms, doctors prefer CT scan images for assessing the progress of disease, but for subsequent repeated examination they prefer CXRs over CT images due to high radiations in CT scan. Therefore, both kinds of images can be used depending upon the condition of the patient. Moreover, due to overlap between CT scan appearance of COVID-19 pneumonia and viral pneumonia, CT examinations need to be integrated with clinical measures for the detailed evaluation (Lee et al. 2020; Zhao et al. 2020). Even, it is difficult for a radiology specialist to detect the nascent stage of COVID-19 because of CXRs peripheral distribution. In fact, there are many aspects that need to be considered in image analysis, which can affect diagnostic results such as physique of the patient, holding of breath during the scan, the presence of other medical devices on the chest and type of projection etc (Tartaglione et al. 2020).

Automated decision-making tools based on machine learning and deep learning techniques could be valuable in alleviating some of this burden (Shen et al. 2017; Litjens et al. 2017). Artificial intelligence in medicine provides facilities for early diagnosis and decision making for further treatment of various diseases (Faust et al. 2018). Therefore, in this paper, a light weight deep learning model is proposed which helps in distinguishing and identifying non-COVID-19 viral, bacteria and other pathogens from COVID-19 pneumonia. For the applying deep learning model, open source lungs X-ray and CT scan images database developed by of Cohen et al. (2020); Zhao et al. (2020) is used. In Fig. 1 representative chest X-rays of healthy and COVID-19 patients are given.
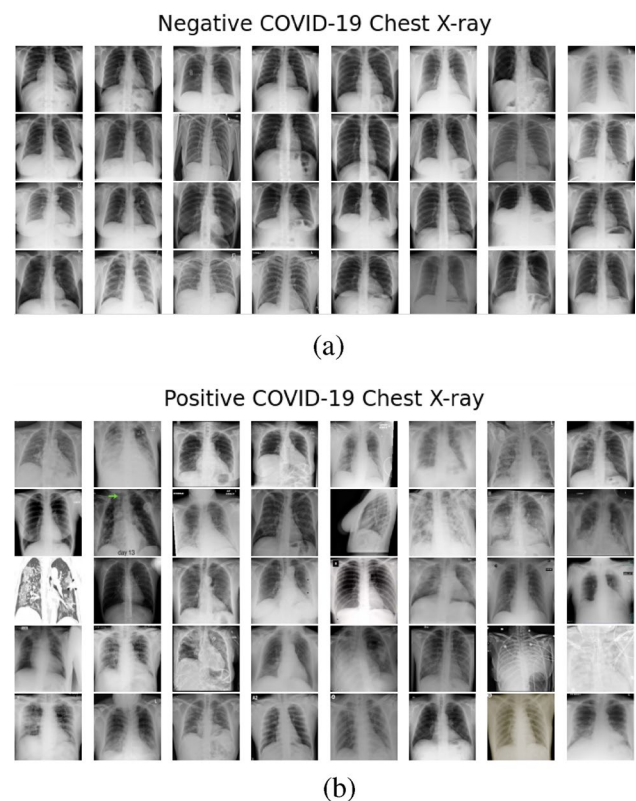

Fig. 1 Representative chest X-ray images for healthy and COVID-19 patients

Since publicly limited COVID-19 CXR and CT scan image data are available. Therefore, to increase the data, extra artificially data is generated via data augmentation. The proposed model helps us to predict and differentiate between COVID-19 and non-COVID-19 patients, initiating a quick screening of the virus, resulting in timely separation and treatment to cease further outspread of the virus. The major contributions of this research paper are as follows:

- To overcome the insufficient data, extra artificial data is generated using data augmentation.
- Before feeding images into the deep learning model, images are pre-processed using technique proposed by Pasa et al. (2019).
- Pre-trained InceptionV3 deep learning model (Szegedy et al. 2016) is used for classifying COVID-19 and Non-COVID images.
- The acquired results have been assessed using well-known parameters such as area under the ROC curve, model loss, confusion matrix, and training accuracy.
- The proposed model accurately predicts the COVID-19 CXRs images with an accuracy of 96% and CT scan images with an accuracy of 93%.

- The proposed model is compared with other deep learning models like VGG 16 (Visual Geometry Group) (Simonyan and Zisserman 2014) used by Panwar et al. (2020) for COVID-19 detection, by ResNet50V2 Model (He et al. 2016) and other existing deep learning models. It is found to be better in terms of accuracy and other performance parameters.
- A web application has been developed on the proposed model using JavaScript, which helps in detecting COVID-19 on the basis of uploaded CT scan or CXR image.

2 Related works

Recently, machine learning methods and deep learning models have gained popularity due to their promising results without human intervention. These models are automated, robust, accurate and helps in detecting and classifying diseases using medical images. Since the emergence of SARS-COVID-19, many deep learning models have been proposed, some of which are summarized in this Section.

In Ahsan et al. (2020), Mulilayer Preceptron-Convolutional Neural Network is proposed in which mixed data (CXRs images, numeric/categorical data) is used for COVID-19 diagnosis. In this model, various optimizers such as Stochastic gradient descent (Sgd), Adaptive learning rate optimization algorithm (Adam), and Root mean square propagation (Rmsprop) are used both for a balanced and imbalanced data set. E. Luz et al. proposed EfficientNet architecture (Luz et al. 2020) for COVID-19 screening, which requires low computational power. The model is also evaluated for cross data set to assess its generalization power. In Ozturk et al. (2020), DarkCovidNet architecture is proposed in which 17 convolutional layers are used and different filtering is used in each layer. The model multiclassify between COVID-19, non-COVID and Pneumonia using CXRs raw images with an accuracy of 87.02%. However, the data set used is very small in size. Hemdan et al. proposed COVIDX-Net (Hemdan et al. 2020), a deep learning framework. The framework consists of seven different deep convolutional neural network architectures to analyze the normalized intensity of CXRs to classify the image for COVID-19. In Narin et al. (2020), five pre-trained CNN (Convolutional Neural Network) architectures have been proposed. In the proposed model, three binary classifications out of four classes, namely COVID-19, healthy, viral pneumonia and bacterial pneumonia are implemented. Among them, it is shown that ResNet50 provides the highest classification accuracy.

Zhou et al. (2021) proposed an ensemble deep learning model in which three pretrained classifiers namely AlexNet, GoogleNet and ResNet are used on CT scan images. The ensemble classifier is obtained using the relative majority voting method. Chen et al. (2020) introduced a deep learning algorithm which segments the multiple infected regions of COVID-19 CT scan images. The algorithm based on U– net architecture makes use of aggregate residual transformations for the better feature representation. In the study conducted by Ni et al., a deep learning model is proposed in which three stages, namely abnormality detection, pulmonary lobe segmentation, and voxel segmentation are used for COVID-19 detection using CT scan images (Ni et al. 2020). In Rahimzadeh et al. (2021), feature pyramid network is applied along with ResNet50V2 model so that the model can be able to detect disease from the images with different resolutions. Song et al. (2021) proposed a deep learning architecture for CT scan images in which firstly, the main region of the lungs is extracted, then Details Relation Extraction Neural network (DRENet) is designed to get the image-level predictions. In the third stage, image level scored results are aggregated for the prediction of COVID-19 at a personal level.

Many approaches have been proposed in the literature based on CNN, which helps in the quick diagnosis of COVID-19 and many other diseases (Ghaderzadeh and Asadi 2021; Hafeez et al. 2022; Saad et al. 2022). Each approach has its own pros and cons. We, hereby, present an extension of existing techniques for detecting COVID-19 using both CT scan and CXRs images. The presented model is light weight, therefore, a web application is also developed for the proposed model which gives a single platform to the end user for examining their both CT scan or CXR images for COVID-19.

3 Materials and methods

3.1 Data set and pre-processing

In this study, image data set has been acquired from the open source repository outsourced by Dr. Joseph Cohen and by Cohen et al. (2020); Zhao et al. (2020). This data source is constantly being furnished with new data generated by various bodies around the globe. The same dataset is utilized by many researchers for detecting and analyzing COVID-19 patients. At the time of this study 920 X-ray and 746 CT scan images have been used for analysis and data set is organized into two categories COVID-19 and non-COVID-19.

Since the data set is formed by contributions from various sources, therefore, images are in a variety of sizes depending upon the imaging equipment used. In this study, images have been resized to the square form before feeding to the model. Resizing may cause distortion of the image leading to suppression of useful data. In order to avoid distortion, a pre-processing technique proposed by Pasa et al. (2019)

(a) original CXR image with COVID-19 ;

(b) Pre-processed image in a square shape.

Fig. 2 Pre-processing of the image

is used for taking out the middle part and removing black bands. Fig. 2 depicts a pre-processed image to which the following operations have been applied:

- Black bars appearing at the borders are eliminated.
- The dimensions of the image are altered till the smallest border size becomes up to 224 pixels.
- Middle region of 224 X 224 X 3 pixels is extracted

Further, all sets of images are normalized and dataset is transformed into Gaussian (normal) distribution $N(0, 1)$, i.e, mean value $\mu=0$ and variance value $\sigma^2=1$. After that, mean and standard deviation values are calculated for the dataset. Then whole data set (training, testing and validation sets) is normalized by adding mean value and dividing by the calculated value of standard deviation.

3.1.1 Data augmentation

Deep-learning models often present better results with a large set of images. Since data set used in the present study is less, therefore, data augmentation is used to produce more data based on the available training set. In this study, augmentation is performed by ;

(1) Rotating image randomly within the range of $\pm$ 20 degrees
(2) Performing image shifting in the range of around $\pm$ 20%. and

Original COVID-19 image   Image after Data Augmentation

Fig. 3 Image after data augmentation

(3) Horizontal flipping.

Original X-ray image and image after augmentation is shown in Fig. 3

3.2 Proposed model

Neural Networks (NN) have recently shown outstanding results over classical machine learning techniques with large, high dimensional and unstructured data containing all kinds of data such as text, image, categorical and numerical etc (Nakada and Imaizumi 2019). The emergence of Convolutional Neural Networks (CNN), a category of deep neural networks, has revolutionized artificial intelligence (Krizhevsky et al. 2012). The word deep means increase in the size of the network with increased number of layers and the convolutional word indicates that the network make use of mathematical operator convolution. A convolution network consists of three components convolution layer, pooling layer and output layer. Convolution layer extracts the features of the image such as colors, edges, etc. depending upon the problem in hand. Pooling layer helps in reducing the trainable features for making CNN computationally efficient. Output layer accomplishes the task of recognition or classification after getting an output of the convolution or pooling layer. CNN model is created by one or more fully connected layers.

The deep NN provides an opportunity to develop a robust model, both for small and large data sets. Instead of developing a model from scratch, existing proven deep learning model is used in the present study. To design our model, GoogLeNet InceptionV3 (Szegedy et al. 2016) network, the winner of the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2014 (an image classification competition), is chosen. The inception network helps in increasing the accuracy and decreasing the computational effort by replacing the fully connected network (many layers in depth) by the sparsely connected network architecture. Naive version of inception module and with dimensionality reduction is shown in Fig. 4. In the naive version merging
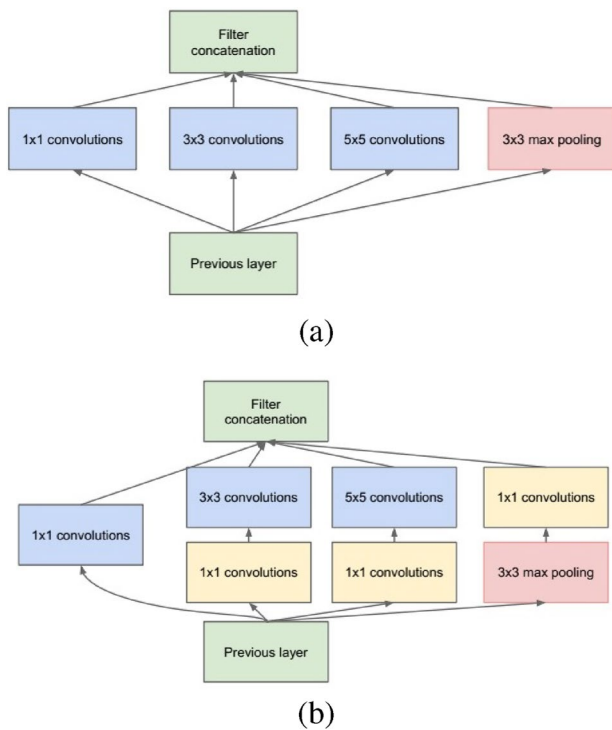
(a)

(b)

Fig. 4 Inception module (Szegedy et al. 2015) **a** Naive version **b** With dimensionality reduction
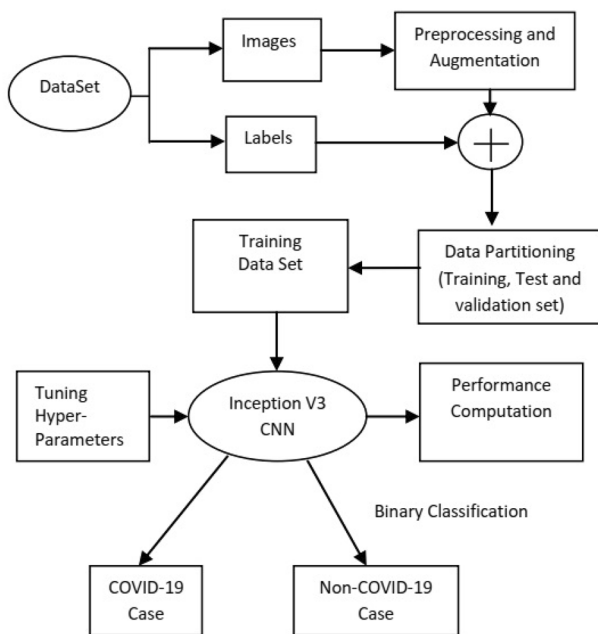

Fig. 5 Proposed deep learning model

of the output of the pooling layer with outputs of the convolutional layer leads to computational increase within a few stages while in dimensionality reduction 1×1 convolutions

are used to compute reductions before the expensive 3×3 and 5×5 convolutions (Szegedy et al. 2015).

Inception V3 is 48 layers deep and makes use of RMSprop optimizer, batch normalization and 7×7 factorized convolution. The final proposed model is shown in Fig. 5

Algorithm 1 describes the proposed model in detail.

Algorithm 1 Proposed Algorithm

1: **Input data:** COVID-19 Chest X-ray & CT Scan Images (X, Y); where Y = {y / y ε {COVID; NON-COVID}}
2: **Output data:** Trained transfer model that detected the COVID-19 Chest X-ray & CT Scan image x ε X
3: **Pre-Processing Steps**
4: Modify the X-ray and CT Scan input to dimension 224 height X224 width
5: Generate X-ray and CT-scan Image using data augmentation
6: Mean normalize each X-ray and CT scan image
7: Download and reuse transfer model d={inceptionV3}
9: μ=0.001
10: for epochs 1:500 do
      foreach mini-batch (X_i, Y_i) ε $(X_{train}; Y_{train})$ do
          Modify the coefficients of transfer d(.)
          If error rate increases for five epochs then μ=μ*0.001
      end
   end
   end

In the algorithm, d is the transfer model InceptionV3. Transfer model is trained with the COVID-19 X-ray and CT scan images data set (X, Y) ; where X is the set of N input data, each of size, 224 height $\times$ 224 width (Pre-processed image), and $Y = \{ y \; y\epsilon\{COVID-19, Non-COVID-19\}$. The size of the data set is increased using data augmentation and images are normalized. Further, the data set is divided into a training set $(X_{train}; Y_{train})$ and test data in the ratio of 80:20, i.e, 80% training data and 20% test data, further, 10% of the test data is considered as validation data. μ is learning rate that indicates that how fast a model accustoms to the problem. To process images, training data is partitioned into mini-batch of size n=32 such that $(X_p; Y_p)\epsilon(X_{train}; Y_{train})$; $p = 1, 2, 3 \dots \frac{N}{n}$. The transfer model d is iteratively optimized to reduce the functional loss given in Eq. (1).

$$C(w, X_i) = \frac{1}{n} \sum_{x \epsilon X_i, y \epsilon Y} c(d(x, w), y), \qquad (1)$$

where $d(x, w)$ is the InceptionV3 model that outputs label y for given input x and weight w and c(.) is the binary entropy loss function.

3.3 Performance metrics

The model is evaluated for the well know deep learning metrics such as precision, recall and F1-score. These parameters are calculated on the basis of a confusion matrix which consists of the following parameters

True Positive (TP) = COVID-19 Patient classified as a patient.

True Negative (TN) = Healthy individual classified as healthy.

False Positive (FP) = Healthy individual classified as patient.

False Negative (FN) = COVID-19 Patient classified as healthy.

The various deep learning metrics are calculated as:

$\text{Sensitivity} = \frac{TP}{TP+FN} * 100,$

$\text{Specificity} = \frac{TN}{TN+FP} * 100,$

$\text{Precision} = \frac{TP}{TP+FP} * 100,$

$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN},$

$\text{F1} - \text{score} = \frac{2 \times \text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}},$

where sensitivity is recall or true positive rate which measures how good the model is in predicting events in positive class. Specificity is true negative rate, i,e, fraction of actual negatives that are correctly recognized. Precision is that how apt the model is assigning positive events to the positive class. Accuracy means how much correct predictions have been done. F1 score is the harmonic mean of precision and recall. It shows the balance between precision and recall.

ROC (Receiver Operator Characteristic) curve is a two-dimensional plot between true positive rate and true negative rate. It indicates the trade-off between sensitivity and specificity. The ROC curve is measured by Area Under Curve (AUC). Its value lies between 0 and 1. ROC value close to 1 indicates high sensitivity and specificity. In the medical field, ROC curve analysis is done for exploring the performance of the diagnosis (Siddiqui et al. 2020). The AUC is found by the well-known trapezoidal rule in which area is divided into sections of equal width. Then sum of area of different sections is found just like integration of points - (p, q) in a functional form in which points are divided into n equal parts such that $x_0 = p$, $x_n = q$, and $x_m = x_0 + m(\frac{p-q}{n})$ Panwar et al. (2020). The sum of the area of different section under the trapezoid is given in Eq. 2,

$$T(p,q,n) = \left(\frac{p-q}{n}\right) \times \left(\frac{f(p)-f(q)}{2}\right) \times \left(\frac{f(p)-f(p-q)}{n}\right). \tag{2}$$

This is an effective method for calculating AUC under ROC.

4 Experimental results

The introduced model is programmed using Python 3.6 programming language. For training the model, benefit of the free online Linux environment called Google Colaboratory is availed (Bisong 2019). For finding the experimental results, we have used Intel i5 processor with 16GB RAM and HD 620 graphic unit. The dataset consists of around 920 chest X-ray images and 746 CT scan images for classification purposes. The images are classified into two classes COVID and Non-COVID. The data set is partitioned in 80:20 ratio with 80% training data and 20% test data. The InceptionV3 model consists of symmetric and asymmetric building blocks, including convolutions, max pooling, average pooling, concatenations, dropouts, and fully connected layers. Batch normalization is applied rigorously throughout the model. Loss is computed using the Softmax function. The architecture of InceptionV3 is shown in following Fig. 6

The batch-wise processing of InceptionV3 model is described in the Table 1.

The proposed model is trained for 500 epochs and learning rate is set at 0.001.

4.1 Results CT scan

Figures 7 and 8 represent the proposed model accuracy, loss for CT scan images. Figures 7 and 8 are complementary to each other. With increasing epoch, training and testing accuracy are increasing and loss is decreasing. Initially sharp lows and ups can be attributed to small data set, however,

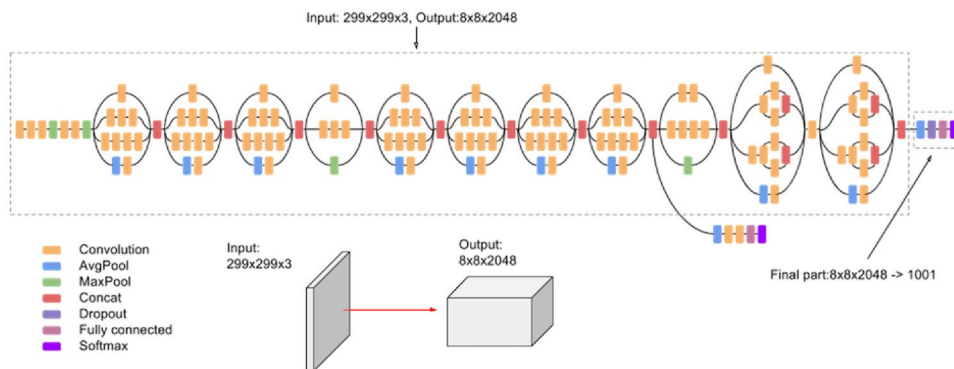**Fig. 6** Architecture of inceptionV3 model (Szegedy et al. 2016)

Table 1 Batch-wise implementation of the proposed algorithm representing processing layer, produced output shape of image, number of parameters learned at the layer and input layer respectively)

```
Model: "model"
_____
Layer (type)                    Output Shape         Param #    Connected to
===============================================================================
input_1 (InputLayer)            [(None, 224, 224, 3) 0

conv2d (Conv2D)                 (None, 111, 111, 32) 864        input_1[0][0]

batch_normalization (BatchNorma (None, 111, 111, 32) 96         conv2d[0][0]

activation (Activation)         (None, 111, 111, 32) 0          batch_normalization[0][0]

conv2d_1 (Conv2D)               (None, 109, 109, 32) 9216       activation[0][0]

batch_normalization_1 (BatchNor (None, 109, 109, 32) 96         conv2d_1[0][0]

activation_1 (Activation)       (None, 109, 109, 32) 0          batch_normalization_1[0][0]

conv2d_2 (Conv2D)               (None, 109, 109, 64) 18432      activation_1[0][0]

batch_normalization_2 (BatchNor (None, 109, 109, 64) 192        conv2d_2[0][0]

activation_2 (Activation)       (None, 109, 109, 64) 0          batch_normalization_2[0][0]

max_pooling2d (MaxPooling2D)    (None, 54, 54, 64)   0          activation_2[0][0]

conv2d_3 (Conv2D)               (None, 54, 54, 80)   5120       max_pooling2d[0][0]

batch_normalization_3 (BatchNor (None, 54, 54, 80)   240        conv2d_3[0][0]

activation_3 (Activation)       (None, 54, 54, 80)   0          batch_normalization_3[0][0]

conv2d_4 (Conv2D)               (None, 52, 52, 192)  138240     activation_3[0][0]
.
.
.

activation_85 (Activation)      (None, 5, 5, 320)    0          batch_normalization_85[0][0]

mixed9_1 (Concatenate)          (None, 5, 5, 768)    0          activation_87[0][0]
                                                                activation_88[0][0]

concatenate_1 (Concatenate)     (None, 5, 5, 768)    0          activation_91[0][0]
                                                                activation_92[0][0]

activation_93 (Activation)      (None, 5, 5, 192)    0          batch_normalization_93[0][0]

mixed10 (Concatenate)           (None, 5, 5, 2048)   0          activation_85[0][0]
                                                                mixed9_1[0][0]
                                                                concatenate_1[0][0]
                                                                activation_93[0][0]

flatten (Flatten)               (None, 51200)        0          mixed10[0][0]

dropout (Dropout)               (None, 51200)        0          flatten[0][0]

dense (Dense)                   (None, 2)            102402     dropout[0][0]
===============================================================================
Total params: 21,905,186
Trainable params: 102,402
Non-trainable params: 21,802,784
```

as epochs progress these ups and downs are less and it converges.

Figures 9 and 10 show the confusion matrix and model metrics for the proposed model. In the Figs. 9, 1 represents COVID positive case and 0 represents Non-COVID case. A good classification model should have balance between precision and sensitivity. Figure 9 shows that the proposed model is having true positive rate, i.e, sensitivity of 89.81% and specificity (true negative rate) of 96.84%. This signifies that COVID-19 in infected patient CT scan can be diagnosed with an error of 6.9%. F1 score of Fig. 10 shows the balance between sensitivity and specificity. The accuracy of the proposed model is 93% which surely will increase with the increased data.

Figure 11 shows the ROC curve. The AUC under ROC curve in the Figure 11 is above the threshold value and calculated as 0.725. This value indicates a good rank of classification.
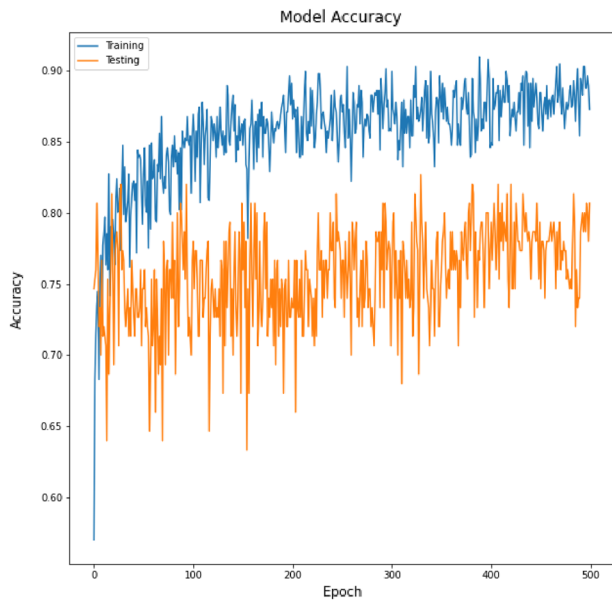
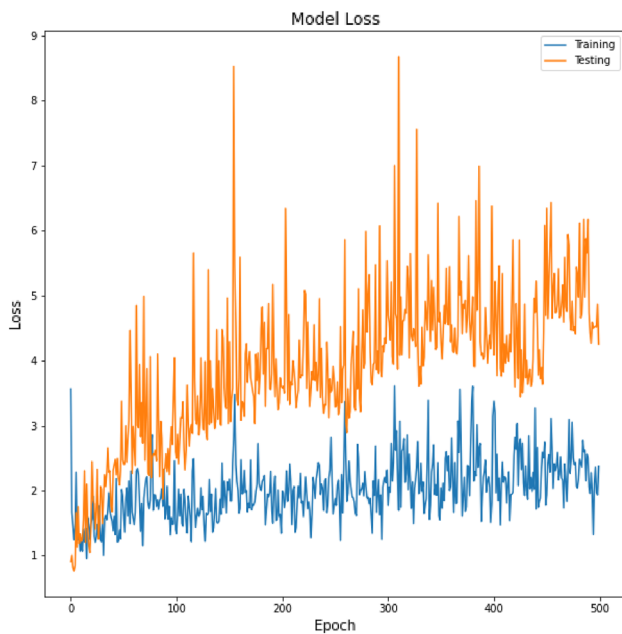**Fig. 7** Model accuracy (with CT scan images)

Fig. 9 Confusion matrix CT scan images

Fig. 10 Model metrics (CT scan, 1-COVID, 0-NonCOVID)

Fig. 8 Model loss with CT scan images

4.2 Results CXRs

Figures 12 and 13 represent the proposed model accuracy, loss for CXRs images. Again, Figs. 12 and Fig. 13 are complementary to each other. As the number of epoch increase, training and testing accuracy is increasing and
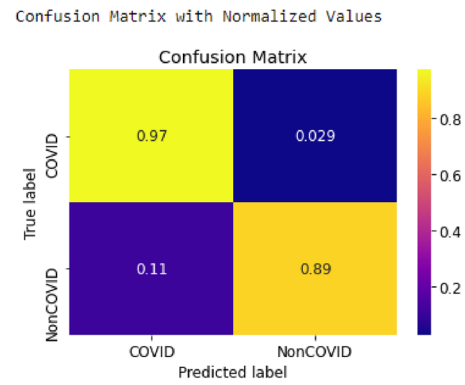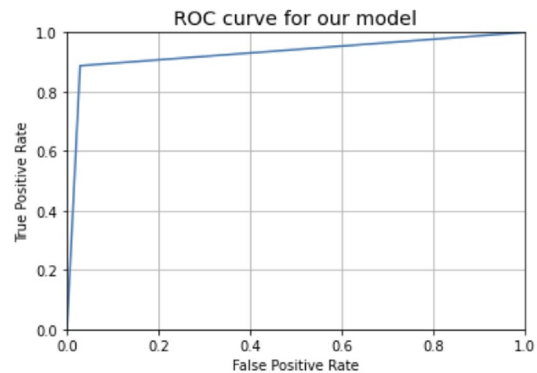

Fig. 11 ROC curve (CT scan images)

loss is decreasing. Initially in CXRs, lows and ups are more sharper as compared to CT scan images. This is due to the presence of outliers in the dataset. However, eventually, as the model learns it converges.

Figure 14 shows the confusion matrix for the proposed model of CXRs data. The accuracy of the proposed model for CXRs is 96%, which is more than that of CT scan images. This is due to the fact that in the present study CXR images are more that the CT scan images. Figure 15 shows that the proposed model for CXRs is having true positive rate, i.e, sensitivity of 93.48% and specificity (true negative rate) of 98.83%. This implies a person that is not infected with COVID can be detected with an error of 4%.
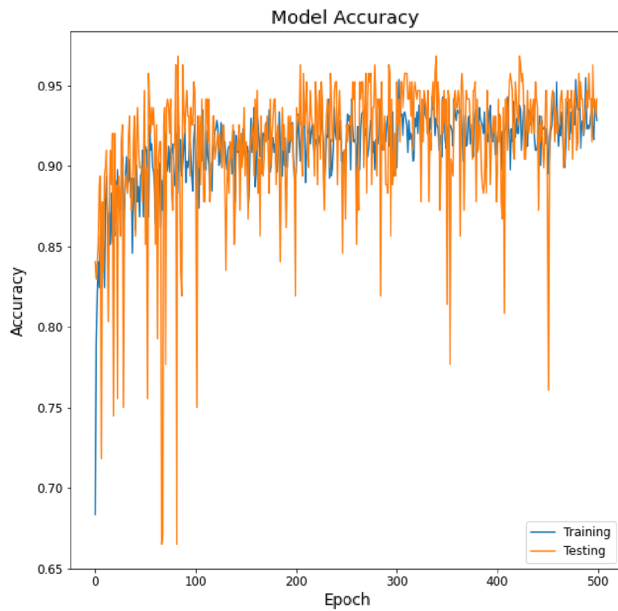
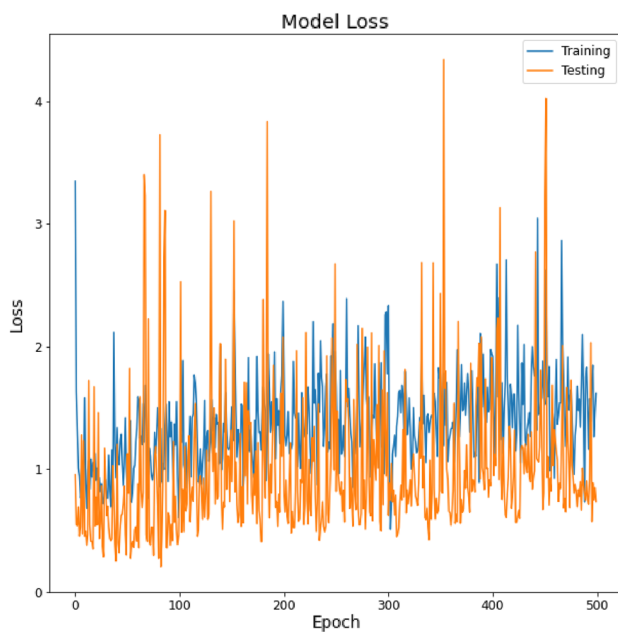**Fig. 12** Proposed model accuracy (with CXRs)

Fig. 13 Proposed model loss (with CXRs)

F1 score value of 0.96 of the proposed model indicates a good classification model.

Figure 16 shows ROC (Receiver Operator Characteristic) curve. The plotted AUC under the ROC curve is calculated as 0.886 which is above a threshold value. The AUC value above the threshold value is considered as excellent in the field of medical diagnosis (Siddiqui et al. 2020; AS and Korsten 2007).
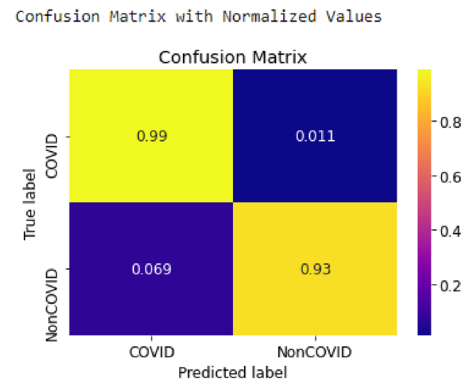

Fig. 14 Confusion matrix (CXRs)

```
            precision    recall   f1-score

        0       0.92       0.99       0.96
        1       0.99       0.93       0.96

 accuracy                             0.96
```

Fig. 15 Performance metrics (CXRs, 1-COVID, 0-NonCOVID)

Fig. 16 ROC curve (with CXRs)

```
            precision    recall   f1-score

        0       0.81       1.00       0.89
        1       1.00       0.80       0.89

 accuracy                             0.89
                    (a)

            precision    recall   f1-score

        0       0.92       0.74       0.82
        1       0.82       0.95       0.88

 accuracy                             0.86
                    (b)
```
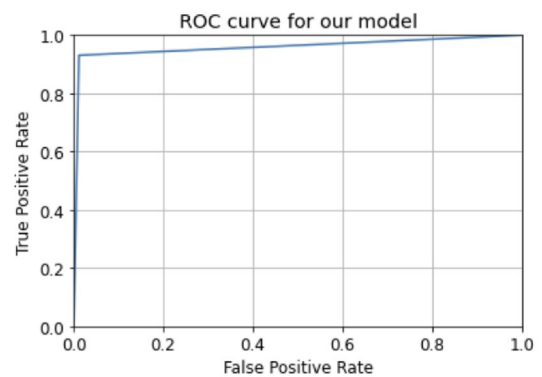
Fig. 17 Performance metrics VGG model (1-COVID, 0-NonCOVID) **a** CXRs **b** CT scan image

```
          precision    recall  f1-score

     0       0.81       0.58      0.68
     1       0.72       0.89      0.80

accuracy                           0.75
```
(a)

```
          precision    recall  f1-score

     0       0.47       1.00      0.64
     1       1.00       0.06      0.11

accuracy                           0.49
```
(b)

Fig. 18 Performance metrics for ResNet model (1-COVID, 0-Non-COVID) **a** CXRs **b** CT scan images

Table 2 Result comparison

Model	Accuracy %age (CXRs)	Accuracy %age(CT Scan Images)
Inception V3	96	93
VGG16	89	86
ResNet50V2	75	49

4.3 Result analysis

To justify the results of the InceptionV3 model, the proposed model is also implemented with other deep learning models such as VGG 16 (Litjens et al. 2017) and ResNet50V2 (Residual Networks) model (He et al. 2016). The VGG 16 model has been used in Simonyan and Zisserman (2014) for COVID -19 detection using CXR images. Performance metrics of these models are shown in Figs. 17 and 18 for CXRs and CT scan images respectively. From Figs. 10, 15, 17 and 18, it can be concluded that, InceptionV3 model has more balanced precision and recall than other models. Table 2 shows the tabular comparison of their accuracy. Table 2 indicates that InceptionV3 performs better and it is computationally efficient because of its dimensionality reduction feature. From Table 2, it is clear that the proposed model extracts the important features from the images in an efficient way as compared to other CNN models. Further, the proposed model is compared with existing models and tabular comparison of their accuracy is shown in Table 3 for CXRs and Table 4 for the CT scan images respectively. Table 3 shows that the proposed model works better than nCOVnet (Simonyan and Zisserman 2014) and CoroNet (Khan et al. 2020) in terms of accuracy. The nCOVnet model utilizes VGG16 (Litjens et al. 2017), and the CoroNet deep learning model makes use of pre-trained Xception architecture (Litjens et al. 2017). The accuracy of deep learning depends upon the size of the dataset. Larger the dataset, more the accuracy. In this regard, the proposed model performs a little better than nCOVnet model and significantly better than CoroNet model. Table 4 indicates that the proposed model performs better than the Ctnet-10 model (Shah et al. 2021) and the model proposed by Wu et al. (2020) for CT scan images. The Ctnet-10 model is self-developed model and model proposed by Wu et al. makes use of ResNet50 (He et al. 2016). This improvement can be attributed to the fact that dataset size is increased via data augmentation. From the obtained results, it is observed that the proposed model can provide a better replacement for the RT-PCR test which takes 4 to 8 hours for revealing out the result.

As far as the complexity of the proposed model is concerned, the InceptionV3 model uses less trainable parameters as compared to VGG 16 and ResNet50 deep learning models. Error rate of InceptionV3 is less as compared to other deep learning models (Alzubaidi et al. 2021). Moreover, the InceptionV3 model makes use of dimensionality reduction, 1×1 convolutions are used to compute reductions before the expensive 3×3 and 5×5 convolutions

Table 3 Comparison with other methods(CXRs)

| Model	Population	Dataset Used	%age Accuracy
nCOVnet Simonyan and Zisserman (2014)	337	Open source Cohen et al. (2020)	88.10
CoroNet Khan et al. (2020)	1300	Open source Cohen et al. (2020) and https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia	89.60
Proposed Model	920	Open source Cohen et al. (2020)	96.00

Table 4 Comparsion with other methods (CT scan)

Model	Population	Dataset Used	%age Accuracy
Wu et al. (2020)	495	Private dataset	81.90
Ctnet-10 Shah et al. (2021)	738	Open Source Zhao et al. (2020)	82.1
Proposed Model	746	Open source Zhao et al. (2020)	93.00

which makes it more computationally efficient (Szegedy et al. 2015).

4.4 Real-time implementation

The benchmark for COVID-19 diagnosis is the RT-PCR test. However, increase in false positive results of the RT-PCR test caused missed infections, which in turn increase the chances of transmission. Sensitivity of RT-PCR depends on a number of factors such as the time span of symptoms, severity of viral infection, the speed of virus reproduction in the respiratory system, the time when the sample taken and the quality of the test process. To overcome this limitation, for a quick diagnosis of COVID-19, a Web application using JavaScript (Smilkov et al. 2019) and Cascading Style Sheets (CSS) is developed. The proposed deep learning model is exported into the JavaScript and used for the development of web application. In this application, user will upload its CT scan or CXR image and would be able to find the results within a fraction of seconds. Fig. 19 shows the user interface and detection results.

The limitation of this web application is that when images are not vivid and have a bad orientation in terms of visibility of the frontal part of the human lungs, then there is a decrease in the accuracy of correct analysis for coronavirus.
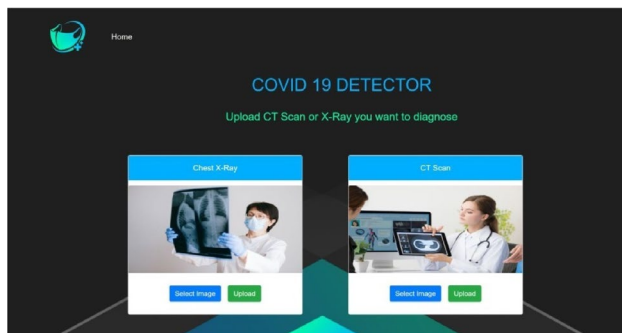
(a) User Interface
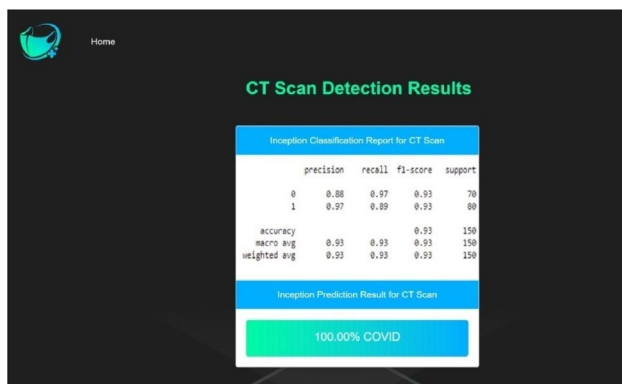
(b) Detection Results

Fig. 19 Web application for the proposed deep learning model

5 Discussion

Artificial Intelligence (AI) based systems play a major role in early detection of COVID-19 and for finding the severity of the disease. In this study, we have proposed a lightweight deep learning model which makes use of Pre-trained CNN IncetptionV3. This model has been applied on CXRs and CT scan images. The performance of deep learning models depends upon the large dataset. These images were pre-processed using the technique proposed by Pasa et al. (2019) before feeding into the model. The major challenge in this study was the lack of a large COVID -19 dataset. To overcome this challenge, image augmentation has been done. In image augmentation, images are artificially generated using shifting, flipping and rotation. The obtained dataset is further partitioned into training and test data set in the ratio of 80:20 respectively. In order to train the model, pre-trained InceptionV3 model (Szegedy et al. 2016) is utilized. The introduced model is implemented using Python 3.6 programming language.

The model shows an accuracy of 93% and precision of 97% for the CT scan images. For CXR images, it shows an accuracy of 96% and precision of 99%. Table 2 shows the accuracy comparison of the proposed model with other deep learning models VGG16 and ResNet50V2 both for CXR and CT scan images . The proposed model performs better than the VGG 16 model and ResNet50V2 model. This due to the fact that the InceptionV3 model used in the proposed model has a low error rate, uses less trainable parameters and make use of the dimensionality reduction feature. Further, Table 3 and Table 4 show the accuracy comparison of the proposed model with other related studies for CXR and CT scan images respectively. Table 3 shows that the proposed model is little better in terms of accuracy than the existing nCOV-net model (Simonyan and Zisserman 2014) from the datasize point of view. However, it is significantly better than Coro-Net model (Khan et al. 2020) for CXR images even though the dataset size of CoroNet model is larger than the datasize used in the present study. It also shows better performance than Ctnet-10 (Shah et al. 2021) and model proposed by Wu et al. (2020) for CT scan images. These results will definitely improve with the increased dataset. From Table 3 and IV, it is clear that the proposed model learned the COVID-19 infections very well leading to fewer false detections. Moreover, existing models are more complex than the proposed model due to the small filter size used in InceptionV3 model. Since the proposed model is lightweight, a web application has been developed by exporting the model into JavaScript. In this web application, users have to upload their CT scan or CXR image and will get results in a fraction of seconds. The benefits of the proposed model are less complex, more accuracy, less memory requirements, computationally efficient

and provides a single solution both for CXRs and CT scan images which makes it apt for mobile and laptops. However, the developed web application shows a decrease in accuracy if the images are not properly oriented in terms of the frontal part of the human lungs.

The limitation of this study is the lack of a large dataset and computational resources as the open source Google Colab platform has been used for implementation. Further, COVID-19 lungs images look alike Pneumonia lungs images. This study can be extended for the 3-class classification, i.e, COVID-19 Vs. Pneumonia Vs. Normal or multi-class classification considering other types of pneumonia and pathogens. The proposed model can be made more accurate, robust and fast with the large dataset.

6 Conclusion and future scope

The best and proven way of controlling the COVID-19 pandemic is social distancing and rigorous testing. There are no specific symptoms for the infected patient. Moreover, it takes 4-10 days for getting specific symptoms such as flu, fever, headache, etc. Majorly, two types of tests are conducted worldwide, i.e, RT-PCR test and antibody test. The antibody test is too much slow to control pandemic and RT-PCR test also has its own limitations and sometimes gives false positive results. CT scans and CXRs are the most fast and efficient diagnosis approach. However, there are no specific quantified diagnosis criteria and dearth of experienced radiologists too. Therefore, the need arises for an automated decision-making tool based on artificial intelligence.

In this study, a deep learning model is proposed which helps in detecting and classifying COVID-19 cases using the CXRs and CT scan images. The model is fully automated and able to detect COVID-19 cases without human intervention. The developed model detects COVID-19 with an accuracy of 93% and 96% for CT scan and CXRs images respectively. Surely, this accuracy will increase with the increased number of samples. The model is also found to be more accurate, with less computing complexity than well-known deep learning model like VGG 16, ResNet50V2 and other existing deep learning models. The developed web application can detect COVID -19 within a fraction of seconds which will definitely help both public and radiologists. The web application of this model provides a single platform for both CXRs and CT scan images.

In the future, we intend to make model more robust, accurate and fast with large set of images. Since it is difficult to distinguish between CT manifestations of COVID-19 pneumonia from the classic pneumonia due to overlap.

Therefore, this work can be extended for the multi-class classification considering COVID-19 pneumonia, viral pneumonia, bacterial pneumonia and normal images. Further, the proposed model can be made more accurate, robust and fast with the large dataset.

Declarations

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