Can AI help in screening Viral and COVID-19 pneumonia?

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Abstract: Coronavirus disease (COVID-19) is a pandemic disease, which has already infected more than half a million people and caused fatalities of above 30 thousands. The aim of this paper is to automatically detect COVID-19 pneumonia patients using digital x-ray images while maximizing the accuracy in detection using image pre-processing and deep-learning techniques. A public database was created by the authors using three public databases and also by collecting images from recently published articles. The database contains a mixture of 190 COVID-19, 1345 viral pneumonia and 1341 normal chest x-ray images. An image augmented training set was created with 2500 images of each category for training and validating four different pre-trained deep Convolutional Neural Networks (CNNs). These networks were tested for the classification of two different schemes (normal and COVID-19 pneumonia; normal, viral and COVID-19 pneumonia). The classification accuracy, sensitivity, specificity and precision for both the schemes were 98.3%, 96.7%, 100%, 100% and 98.3%, 96.7%, 99%, 100%, respectively. The high accuracy of this computer-aided diagnostic tool can significantly improve the speed and accuracy of diagnosing cases with COVID-19. This would be highly useful in this pandemic where disease burden and need for preventive measures are at odds with available resources.

Introduction:
Coronavirus disease (COVID-19) is an infectious disease and looking at the extent of its spread throughout the world, it has been declared as a pandemic by the World Health Organization (WHO) on 11th March 20201. The pandemic declaration also stressed the deep concerns of the alarming rate of spread and severity of COVID-19. It is the first recorded pandemic caused by any coronavirus. It is defined as a global health crisis of its time and it has spread all over the world. Governments of different countries are imposing border restrictions, flight restrictions, social distancing, and increasing awareness of hygiene. However, the virus is still spreading at very rapid rate. Most of the people infected with the COVID-19 experienced mild to moderate respiratory illness, while some developed a deadly pneumonia. There are assumptions that elderly people with underlying medical problems like cardiovascular disease, diabetes, chronic respiratory disease, renal or hepatic diseases and cancer are more likely to develop serious illness2. Until now, there is no specific vaccine or treatment for COVID-19. However, there are many ongoing clinical trials evaluating potential treatments. About 668,351 infected cases were found in 195 countries until 29th March 2020, where 31,027 deaths, 142,853 recovered, 469,092 mild and 25,379 critical cases were found3, 4.

It has been stated that in order to combat with the spreading of COVID-19 disease effective screening of patients and immediate medical response for the infected patients is a crying need. The gold standard screening method used for testing the COVID-19 patients is the Reverse Transcription Polymerase chain reaction (RT-PCR) test on respiratory specimens5. This technique is the most commonly used method of
testing for COVID-19 detection but is manual, complicated, laborious and time-consuming process with a positivity rate of only 63 %6. Moreover, there is a significant shortage of its supply, which leads to delay in the disease prevention efforts6. There are many countries of the world which are suffering with incorrect detection/count of the number of patients with COVID-19, which is due to not all the patients being tested and also due to delay in the test results7. These delays can lead to infected patients interacting with the healthy patients and infecting them in the process. It is stated that the RT-PCR kit costs about USD 120-USD 130 and also requires a specialized biosafety lab to house the PCR machine, each of which may cost USD 15,000 to USD 90,0008. Such expensive and delayed test results is leading to spread of the disease and making the scenario worst. This is not only an issue for low-income countries but also certain developed countries are struggling to tackle with this9. The other diagnosis tools of COVID-19 can be clinical symptoms analysis, epidemiological history and positive radiographic images (computed tomography (CT) /Chest radiograph (CXR)) as well as positive pathogenic testing. The clinical characteristics of severe COVID-19 infection is that of bronchopneumonia causing fever, cough, dyspnea, and respiratory failure with acute respiratory distress syndrome (ARDS)10-13. Readily available and radiological imaging is another major diagnostic tool for COVID-19. The majority of COVID-19 cases have similar features on radiographic images including bilateral, multi-focal, ground-glass opacities with a peripheral or posterior distribution, mainly in the lower lobes, in the early stage and pulmonary consolidation in the late stage13-19. Although typical CXR images may help early screening of suspected cases, the images of various viral pneumonias are similar and they overlap with other infectious and inflammatory lung diseases. Therefore, it is difficult for radiologists to distinguish COVID-19 from other viral pneumonias. The symptoms of COVID-19 being similar to viral pneumonia can sometimes lead to wrong diagnosis in the current situation, where hospitals are overloaded and working round the clock. Therefore, incorrect diagnosis can lead to a non-COVID viral Pneumonia being falsely labelled as highly suspicious of having COVID-19 and thus delaying in treatment with consequent costs, effort and risk of exposure to positive COVID-19 patients. Currently many biomedical complications (e.g., brain tumor detection, breast cancer detection, etc.) are using Artificial Intelligence (AI) based solutions20-23.

Deep learning techniques can reveal image features, which are not apparent in the original images. Specifically, Convolutional Neural Network (CNN) has been proven extremely beneficial in feature extraction and learning and therefore widely adopted by the research community24. CNN was used to enhance image quality in low-light images from a high-speed video endoscopy25 and was also applied to identify the nature of pulmonary nodules via CT images, the diagnosis of pediatric pneumonia via chest X-ray images, automated labeling of polyps during colonoscopic videos, cystoscopic image recognition extraction from videos26-29. Deep Machine learning techniques on chest X-Rays are getting popularity as they can be easily used with low-cost imaging techniques and there is an abundance of data available for training different machine-learning models. Concept of transfer learning in deep learning framework was used by Vikash et al.30 for the detection of pneumonia using pre-trained ImageNet models31 and their ensembles. A customized VGG16 model was used by Xianghong et al.32 for lung regions identification and different types of pneumonia classification. Wang et al.33 used a large dataset and Ronneberger et al.34 used image augmentation along with CNN to get better results by training on small set of images. Rajpurkar et al.35 reported a 121-layer CNN on chest X-rays to detect 14 different pathologies, including pneumonia using an ensemble of different networks. A pre-trained DenseNet-121 and feature extraction techniques were used in the accurate identification of 14 thoracic diseases in36. Sundaram et al.37 used AlexNet and GoogLeNet with image augmentation to obtain an Area Under the Curve (AUC) of 0.95 in pneumonia detection.

Recently, several groups have reported deep-learning based COVID-19 pneumonia detection techniques38-40. Shuai et al.39 used deep learning techniques on CT images to screen COVID-19 patients with an accuracy, specificity and sensitivity of 89.5%, 88% and 87% respectively. Linda et al.38 introduced a deep convolutional neural network, called COVID-Net for the detection of COVID-19 cases from the chest X-ray
images with an accuracy of 83.5%. Ayrton\textsuperscript{40} used a small dataset of 339 images for training and testing using ResNet50 based deep transfer learning technique and reported the validation accuracy of 96.2%. However, this study was reporting the detection accuracy of COVID-19 images with normal images on a small dataset. The authors in this paper have prepared a comparatively large database of X-ray images of normal, viral pneumonia and COVID-19 positive pneumonia and made this publicly available so that other researchers can get benefit from it. Moreover, four different pre-trained deep learning networks (AlexNet, ResNet18, DenseNet201, and SqueezeNet) were trained, validated and tested for two different classification schemes in this study. One classification model was trained to classify COVID-19 and normal X-ray images while other was trained to classify normal, viral and COVID-19 pneumonia images.

**Methodology**

Deep convolutional neural networks typically performs better with a larger dataset than a smaller one. Transfer learning can be useful in those applications of CNN where the dataset is not large. The concept of transfer learning uses the trained model from large dataset such as ImageNet\textsuperscript{41} is used for application with comparatively smaller dataset. This removes the requirement of having large dataset and also reduces the long training period as is required by the deep learning algorithm when developed from scratch\textsuperscript{42, 43}.

Although there are a large number of COVID-19 patients infected worldwide, the number of chest x-ray images publicly available online are small and scattered. Therefore, in this work, authors have reported a comparatively large dataset of COVID-19 positive chest X-ray images while normal and viral pneumonia images are readily available publicly and used for this study. A Kaggle database was created by the authors to make the database publicly available to the researchers worldwide and the trained models were made available so that others can get benefit of this study\textsuperscript{44}.

**Database Description:** In this study, we have used posterior-to-anterior image of chest x-ray as this view of radiography is widely used by radiologist in pneumonia diagnosis. Four different sub-databases were used to create one database. Among these two databases were developed by the authors and other two databases were already publicly available in Kaggle and GitHub. In the following section, authors have summarized how this dataset is created:

- **Italian Society of Medical and Interventional Radiology (SIRM) COVID-19 DATABASE:**
  SIRM COVID-19 database\textsuperscript{45} reports 330 COVID-19 positive radiographic images (CXR and CT) with varying resolution. Out of 330 radiographic images, 70 images are chest x-ray images and 250 images are lung CT images. This database is updated in a random manner and until 29 March 2020, there were 63 confirmed COVID-19 cases were reported in this database.

- **Novel Corona Virus 2019 Dataset:**
  Joseph Paul Cohen and Paul Morrison and Lan Dao have created a public database in GitHub\textsuperscript{46} by collecting 179 radiographic images of COVID-19, Middle East respiratory syndrome (MERS), Severe acute respiratory syndrome (SARS) and ARDS from the published articles and online resources. In this database, they have collected 109 COVID-19 positive chest x-ray images and 25 COVID-19 positive lung CT images with varying image resolutions. However, in this study, authors have considered 60 COVID-19 positive chest x-ray images, which are different from the database authors created from different articles.

- **COVID-19 positive chest x-ray images from different articles:**
  GitHub database has encouraged the authors to look into the literature and interestingly more than 1200 articles were published in less than two-months of period. Authors have observed that the GitHub database has not collected most of the x-ray and CT images rather a small number of images were in that database. Moreover, the images in SIRM and GitHub database are in random size depending on the x-ray machine resolution and the articles from which it was taken. Therefore, authors have carried out a tedious task of collecting and indexing the X-ray and CT images from all the recently publicly available articles and online sources. These articles and the radiographic images were then compared
with the GitHub database to avoid duplication. Authors managed to collect 60 COVID-19 positive chest X-ray images from 43 recently published articles\textsuperscript{44}, which were not listed in the GitHub database.

- **Chest X-Ray Images (pneumonia):**
  Kaggle chest X-ray database is a very popular database, which has 5247 chest X-ray images of normal, viral and bacterial pneumonia with resolution varying from 400p to 2000p\textsuperscript{47}. Out of 5247 chest X-ray images, 3906 images are from different subjects affected by pneumonia (2561 images for bacterial pneumonia and 1345 images for viral pneumonia) and 1341 images are from normal subjects. Chest x-ray images for normal and viral pneumonia were used from this database to create the new database.

  Figure 1 shows sample images from the database for normal, COVID-19 pneumonia, and viral pneumonia chest X-ray images.

  ![Sample X-ray images](image)

  **Figure 1:** Sample X-ray image from the dataset: (A) shows normal cases, (B) shows COVID-19 cases, and (C) shows Viral Pneumonia case.

**Algorithm Selection and Pre-processing:** In this study, MATLAB 2019a was utilized to train, evaluate and test four well-known pre-trained deep learning CNNs: AlexNet\textsuperscript{24}, ResNet18\textsuperscript{48}, DenseNet201\textsuperscript{48} & SqueezeNet\textsuperscript{49} to classify the chest x-ray images for two classification problems as mentioned earlier. Figure 2 illustrates the overview of the methodology of this study. The training of the different models was carried out in a computer with Intel® i7-core @3.6GHz processor and 16GB RAM, 2 GB graphics card with graphics processing unit (GPU) on 64-bit Windows 10 operating system. ResNet and DenseNet have different variants however, ResNet18 and DenseNet201 were readily available for Matlab 2019a and therefore used in this study.

![Block diagram](image)

**Figure 2:** Block diagram of the overall system.

Images with and without augmentation were used for this study. In the Table\textsuperscript{1}, summary of images from different sub-datasets were listed. Total number of COVID-19 images was 190 including training and test set. Therefore, 190 x-ray images were randomly selected from normal and viral pneumonia images to
match with COVID-19 images to balance the database. However, image augmentation techniques were applied to make the 130 training COVID-19 x-ray images 20 fold, which resulted to 2600 X-ray images for COVID-19. Therefore, 1300 normal and viral pneumonia images were randomly selected from the database and two-fold images (2600) training images were created for each category using image augmentation. Four ML algorithms were trained and evaluation by five-fold cross validation using the x-ray images with and without image augmentation. Mini-batch gradient descent with 0.9 momentum, 5 mini-batches and learning rate was 0.0003 was used in this study. Testing of four different algorithms was carried out on 60 non-augmented images of different categories to evaluate the performance of each algorithms.

**Table 1:** Details of Training and Test set.

| Database                          | Types                   | No. of Chest x-ray Images | Total (Without augmentation) | Without Augmentation | Augmented total | With Augmentation |
|-----------------------------------|-------------------------|----------------------------|------------------------------|----------------------|----------------|------------------|
| SIRM-ITALIAN45                    | COVID-19                | 70                         | 190                          | 130                  | 60            | 2660             | 2600 60          |
| Novel Corona Virus 2019 Dataset46 | COVID-19                | 60                         | 190                          | 130                  | 60            |                  |                  |
| Database from different articles44 | COVID-19                | 60                         | 190                          | 130                  | 60            |                  |                  |
| Chest X-Ray Images (pneumonia)47  | Normal                  | 1341                       | 190                          | 130                  | 60            | 2660             | 2600 60          |
|                                   | Viral Pneumonia         | 1345                       | 190                          | 130                  | 60            | 2660             | 2600 60          |

**Preprocessing:** One of the important steps in the data preprocessing was to resize the X-Ray images as the image input for different algorithms were different. For AlexNet and SqueezeNet, the images were resized to 227×227 pixels whereas for ResNet18 and DenseNet201, the images were resized to and 224×224 pixels. All images were normalized according to the pre-trained model standards.

**Image augmentation:** As discussed earlier, in this study, authors have utilized three augmentation strategies (Rotation, Scaling, and Translation) to generate 20-fold training set of COVID-19 images while 2-fold normal and viral pneumonia images, as shown in supplementary figure S1. The rotation operation used for image augmentation was done by rotating the images in the clockwise and counter clockwise direction with an angle of 15, 30, 45, 60, 75 and 90 degrees. The scaling operation is the magnification or reduction of frame size of the image and 2.5% to 10% image magnifications were used in this work. Image translation was done by translating image horizontally and vertically by 5% to 20%.

**Visualization of the images in the deep layers:** We investigated the features of the image by observing which areas in the convolutional layers activated on an image by comparing with the matching regions in the original images. The activation map can take different range of values and was therefore normalized between 0 and 1. The strongest activation channels were observed and compared with the original image. It was noticed that this channel activates on edges. It activates positively on light left/dark right edges, and negatively on dark left/light right edges.

Convolutional neural networks learn to detect features like color and edges in their first convolutional layer. In deeper convolutional layers, the network learns to detect features that are more complicated. Later layers build up their features by combining features of earlier layers. Figure 3 shows the activation map in
early convolutional layers, deep convolutional layer and strongest activation channel for each of the models.

Figure 3: Activation map for different network models of (i) first convolutional layer, (ii) strongest activation channel, (iii) deep layer images set, and (iv) deep convolutional layer for that specific image.

Performance Evaluation Matrix: In order to evaluate the performance of different deep learning algorithms for classifying the x-ray images into two schemes, four different algorithms were trained. The trained algorithms were validated using 5-fold cross-validation. The performance of different networks for testing dataset was evaluated using six performances metrics such as- accuracy, sensitivity or recall, Specificity, Precision (PPV), Area under curve (AUC), F1 score.

Results & Discussion

It was observed that SqueezeNet showed the best performance for classifying images from normal and COVID-19 group and in normal, viral pneumonia and COVID-19 group. The comparative performance of training and testing accuracy for different CNNs for two different classification schemes were shown in Supplementary Figure S2 and comparative AUC curve were shown in Supplementary Figure S3. SqueezeNet is producing the highest accuracy of 98.3% for two classification schemes for both training and testing. ResNet18 and SqueezeNet were performing excellent in training dataset. However, SqueezeNet outperforms ResNet18 and other algorithms for test dataset.
Table 2 summarizes the performance matrix for different CNN algorithms tested for the two different classification schemes without image augmentation. DenseNet201 outperforms other models in two different classification schemes in terms of different performance indices when the image augmentation was not employed. However, the performance matrix was significantly improved with image augmentation and it was observed that SqueezeNet outperforms other models in both classification schemes in this case as shown in Table 3.

**Table 2:** Different performance metrics for different deep learning networks for two-class and three-class classification without image augmentation.

| Task                          | Models         | Accuracy | Sensitivity (Recall) | Specificity | Precision (PPV) | Area under curve (AUC) | F1 Scores |
|-------------------------------|----------------|----------|----------------------|-------------|-----------------|------------------------|-----------|
| Normal and COVID-19           | AlexNet        | 0.958    | 0.95                 | 0.967       | 0.966           | 0.992                  | 0.958     |
|                               | ResNet18       | 0.95     | 0.933                | 0.967       | 0.965           | 0.996                  | 0.948     |
|                               | DenseNet201    | **0.967**| **0.95**             | **0.983**   | **0.982**       | **0.99**               | **0.97**  |
|                               | SqueezeNet     | 0.966    | 0.95                 | 0.98        | 0.982           | 0.99                   | 0.969     |
| Normal, COVID-19 and Viral Pneumonia | AlexNet  | 0.94     | 0.93                 | 0.94        | 0.92            | 0.98                   | 0.925     |
|                               | ResNet18       | 0.95     | 0.92                 | 0.94        | 0.95            | 0.99                   | 0.95      |
|                               | DenseNet201    | **0.961**| **0.95**             | **0.967**   | **0.982**       | **0.985**              | **0.965** |
|                              | SqueezeNet     | 0.933    | 0.95                 | 0.925       | 0.98            | 0.981                  | 0.964     |

**Table 3:** Different performance metrics for different deep learning networks for two-class and three-class classification, when image augmentation was used.

| Task                          | Models         | Accuracy | Sensitivity (Recall) | Specificity | Precision (PPV) | Area under curve (AUC) | F1 Scores |
|-------------------------------|----------------|----------|----------------------|-------------|-----------------|------------------------|-----------|
| Normal and COVID-19           | AlexNet        | 0.975    | 0.95                 | 1           | 1               | 0.99                   | 0.97      |
|                               | ResNet18       | 0.967    | 0.933                | 1           | 1               | 0.998                  | 0.965     |
|                               | DenseNet201    | **0.975**| **0.95**             | **1**       | **1**           | **0.993**              | **0.974** |
|                               | SqueezeNet     | 0.983    | 0.967                | 1           | 1               | **0.998**              | **0.983** |
| Normal, COVID-19 and Viral Pneumonia | AlexNet  | 0.954    | 0.93                 | 0.958       | 1               | 0.98                   | 0.955     |
|                               | ResNet18       | 0.95     | 0.95                 | 0.96        | 1               | 0.95                   | 0.974     |
|                               | DenseNet201    | **0.967**| **0.96**             | **0.96**    | **0.983**       | **0.97**               | **0.971** |
|                              | SqueezeNet     | **0.983**| **0.967**            | **0.99**    | **1**           | **0.99**               | **0.983** |

Figure 4 shows the confusion matrix for SqueezeNet for two-class problem and three-class problem with image augmentation. It is clear from Figure 4 that the reduction of accuracy from 100% was due to the miss-classification of two COVID-19 images to normal otherwise this technique would reach 100% accuracy. This was true for both two-class and three-class problems. Moreover, a viral pneumonia was miss-classified to normal in the three-class problem. However, interestingly none of the COVID-19 images was miss-classified to viral pneumonia and vice versa. This is very important, as the computer-aided system (CAD) should not classify any COVID-19 patients to viral pneumonia or vice versa; however, it is important to see why the classifier failed for two COVID-19 patients and miss-classified them to normal.
The difference between normal and COVID-19 x-ray images can be observed in the deep convolutional layer of pretrained CNN model. It is notable that from Figure 5 that the 14th layer of SqueezeNet pre-trained model can detect features that can distinguish normal, COVID-19 and Viral Pneumonia images. This shows the reason of the success of SqueezeNet in detecting COVID-19 X-ray images and distinguishing it from normal and viral pneumonia images, which several groups of researchers reported earlier are not reliably possible by X-ray images.

**Figure 4:** Confusion matrix for classification of (A) Normal and COVID-19, and (B) Normal, COVID-19 and Viral Pneumonia using SqueezeNet.

**Figure 5:** Images of 23rd channel of first convolutional layer (i), 14th convolutional layer (ii) and 29th convolutional layer images of SqueezeNet (iii) for different subject groups: Normal, COVID-19, and Viral Pneumonia. Red arrows in COVID-19 image (ii) shows the regions of light focus edge.
Figure 6 shows two images of COVID-19 with false-negative findings missed by both two- and three-class classifiers. The main reason behind the missing of two COVID-19 images is a less opacity in the left and right upper lobe and suprahilar on posterior-to-anterior x-ray images, which is very similar to normal x-ray images (see Supplementary Figure S4).

![Figure 6: Two COVID-19 images which are miss-classified COVID-19 image by two- and three-class classifier.](image)

It can be summarized that the proposed technique can classify most of the COVID-19 x-ray images very reliably. The algorithm fails if no evident light focus edge feature is appeared in the deep layer and this type of COVID-19 cases have to be confirmed by other techniques.

Conclusion
This work presents deep CNN based transfer learning approach for automatic detection of COVID-19 pneumonia. Four different popular CNN based deep learning algorithms were trained and tested for classifying normal and pneumonia patients using chest x-ray images. It was observed that SqueezeNet outperforms other three different deep CNN networks. The classification accuracy, sensitivity, specificity and precision of normal and COVID-19 images, and normal, COVID-19 and viral pneumonia were (98.3%, 96.7%, 100%, 100%), and (98.3%, 96.7%, 99%, 100%) respectively. COVID-19 has already become a threat to the world’s healthcare system and economy and thousands of people have already died. Deaths were initiated by respiratory failure, which leads to the failure of other organs. Since a large number of patients attending out-door or emergency, doctor’s time is limited and computer-aided-diagnosis can save lives by early screening and proper-care. Moreover, there is a large degree of variability in the input images from the X-ray machines due to the variations of expertise of the radiologist. SqueezeNet exhibits an excellent performance in classifying COVID-19 pneumonia by effectively training itself from a comparatively lower collection of images. We believe that this computer aided diagnostic tool can significantly improve the speed and accuracy of diagnosing cases with COVID-19. This would be highly useful in this pandemic where disease burden and need for preventive measures are at odds with available resources.

Authors Contribution: M.E.H.C, T.R and A.K were involved in creating the database, while experiments were carried by T.R. and M.E.H.C and all authors were involved interpreting, drafting and revising the manuscript.

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Supplementary Materials

Supplementary Figure S1: Original Chest-X-ray image (A), Image after rotation by 45 degree counter clockwise (B), Image after rotation by 45 degree clockwise (C), Image after 20% horizontal and vertical translation (D), and Image after 10% scaling (E).

Supplementary Figure S2: Comparison of training and testing accuracy for Normal and COVID-19 (A), Normal, COVID-19 and Viral Pneumonia (B) classification using different CNN models.

Supplementary Figure S3: Comparison of the ROC curve for Normal and COVID-19 (A), Normal, COVID-19 and viral Pneumonia (B) classification using CNN based models.
**Supplementary Figure S4**: Deep layer images of (A) Normal and (B) COVID-19 samples. Red arrows are showing the regions of abnormality became apparent in the deep layers of COVID-19 images, which was not visible in normal X-ray images.