COVID-19 Classification from Radiography Images using Deep Learning

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***Abstract*—The novel Coronavirus 2019 (COVID-19) continues to spread exponentially, especially in India with total cases crossing 20 lakhs mark as of today. It has deeply affected daily lives, public health, and the economy of the whole world. A vital step in tackling COVID-19 is a successful screening of infected patients as soon as possible and treating them. There is a need for supplementary diagnostic tools apart from RT-PCR, which is easy to use and less contagious. Significant findings have proven that Chest X-rays (CXR) in combination with Deep learning algorithms for Image Processing, are vital in finding infected patients. In this paper we have explored the proposed methodologies of classifying the CXR images taken from various sources into COVID-19 positive and negative classes.**

***Index Terms*—COVID-19 detection, COVID-19 classification, Chest X-ray (CXR), Radiographs, convolution neural networks(CNN), deep learning**

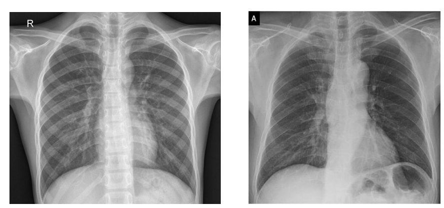
I. Introduction

Coronavirus disease (COVID-19) is a highly infectious disease caused by a newly discovered coronavirus namely "SARS-CoV-2" [1] [2]. Due to its high spreading rate and lack of proper treatment, vaccines, early detection of Covid-19 is crucial and thus flattening the curve to impose less burden on medical resources. Currently, RT-PCR (reverse transcription polymerase chain reaction) [3] is the standard for testing and tracking COVID patients. It is a RNA-based assay using nasopharyngeal swabs which is uncomfortable and costly. Since most of the patients have been diagnosed with pneumonia and lungs related problems, radiological diagnosis may be useful and less costly. CXR do not require intruding the respiratory system thus eliminating spread of virus through air or any risk of spreading. It is convenient, cost effective method that can be combined with AI to classify and detect positive patients up to a certain accuracy [4]. It has been concluded from clinical studies that rapid testing and segregation is the only measure to defeat this virus until we find a proper vaccine for this. Since RT-PCR is a time consuming process and has certain complications, so we should rely on other methods as well [5]. Nowadays many biomedical problems like brain tumor detection, breast cancer detection, etc. are being identified using Artificial Intelligence (AI) based solutions [5] [6]. And given that nearly all hospitals have X-ray imaging machines, it could be possible to use X-rays to test for COVID-19 without the dedicated test kits. Deep learning techniques can help in extracting image features from the X-ray images, which are insignificantly visible through naked eyes. Besides, Convolutional Neural Network (CNN) has been found out to be amazingly helpful in extracting and learning useful features present in the images, which makes it to be widely adopted by the research community [6] [7].

II. Methodology and Dataset description

A. CXR image Collection

Chest X-ray images were collected from different sources and used for the classification algorithm [8] [9]. These images have been complied by various persons some of who are doctors, researchers, clinical persons, etc. Some of the sample images have been depicted in Fig. 1.



(a) (b)

Fig. 1. Sample CXR images: (a) COVID-ve (b) COVID+ve

B. Dataset Description

We have used the datasets that contains CXR images from patients with confirmed COVID-19 disease, common bacterial pneumonia and normal incidents (no infections) [15]. It is a combination of two different publicly available datasets at [8] and [9]. COVID-19 positive cases are taken from Dr. Joseph Cohen's Github repository [9] and consist of 1002 Posterior-Anterior (PA) X-ray images of lungs. In addition, 1341 normal and 3875 Pneumonia (bacterial) and 390 Pneumonia (viral) chest X-Ray images were downloaded from Kaggle's repository [8] [15]. The images from these sources were combined and in total 1032 images were finally selected for the project. The bacterial and normal datasets were chosen for training the model and viral dataset was chosen for testing. Suitable amount of data are available now for us to predict with less error. One should note that, "normal" cases doesn't mean that the person will not get emerging diseases in the near future. It depicts only the normal CXR images without any respiratory disease.

C. Image Pre-processing

The CXR images have been resized so that it fits the algorithm and speeds up the training process. Image resizing and labelling is required so that the training algorithm can justify its importance. Images were also converted to ’gray’ channel.

D. Image Augmentation

CCN requires enough image data for it to work properly and give excellent performance. Techniques like rotation, horizontal flip, vertical flip, translation, etc. provide adequate image data which is good enough to train the CNN model properly and fully [4]. This is necessary as when certain image is fed into the model as test image, then the model must be robust enough to detect and extract features which corresponds to the particular class.

In this study we have changed the input image size to 512-by-512. Images were rotated by 20°, translated by 50 pixels both left and right, top and bottom, and flipped by 180°horizontally.

E. Training Method

Stochastic Gradient Descent algorithm has been used to train the network [4] [10] [11]. The gradient descent algorithm works by updating the weights of the neural network, so that the loss function is minimised. The algorithm takes small steps in the direction of the negative gradient of the loss, converging the results. This algorithm can be given by the equation below.

$$\beta_{l+1} = \beta_l - \alpha \nabla E(\beta_l) \quad (1)$$

where l is the number of iterations, $\alpha > 0$ is the learning rate, β is the parameter vector, and $E(\beta)$ is the cross entropy loss function.The gradient of the loss function, $\nabla E(\beta)$, is evaluated on the entire training dataset [11]. The ’standard’ gradient descent algorithm works on the entire dataset. However, the ’stochastic’ gradient descent algorithm calculates the gradient and updates the parameters on the subset of dataset. When each gradient is evaluated using the subset, it is called an *iteration*. After each iteration, the algorithm moves towards minimizing the loss function by one step. Running the training algorithm, over the entire training dataset, using the ’subsets’, is called an *epoch* [11]. We specify the number of subsets, number of epochs, learning rate and augmentation process for the training, as per dataset size.

III. Architecture of the Deep Learning Model

The model was trained from scratch using the datasets as in [8]and [9]. Basic Deep Learning Network is something like as shown in Fig. 2. It consists of an input layer, hidden layers, and output layer. Hidden layers consists of different layers, each layer having functionality of its own [12].

Convolution layers apply filters to extract features from the image dataset. *Pooling layers* are used to further reduce

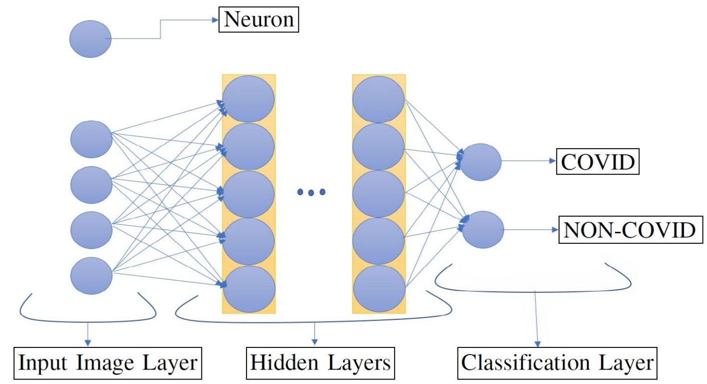


Fig. 2. Basic Deep Learning Network

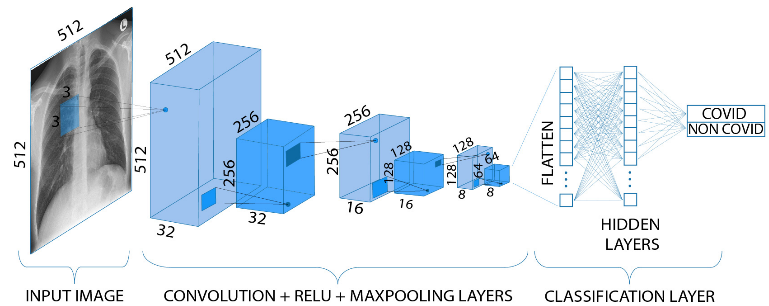


Fig. 3. Deep Learning Network used in the model

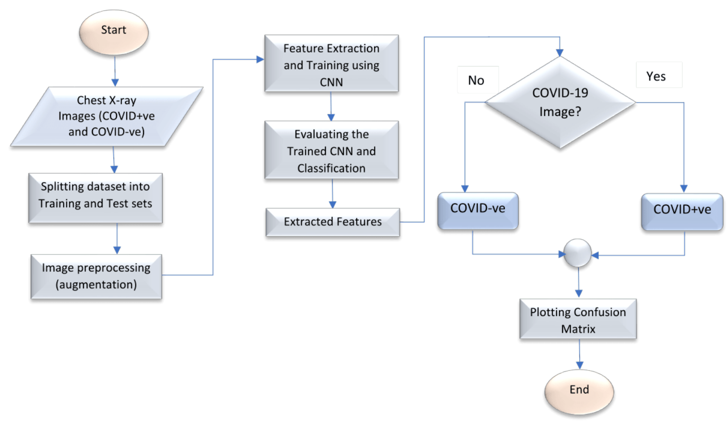


Fig. 4. Flowchart of the proposed model

processing power by using ’max pooling’, which takes the maximum value in a certain filter region, or ’average pooling’, which takes the average value of all the features extracted in a filter region. These methods are used to reduce the dimensionality of the network. *Fully connected layers* collect all the final features and generate final classification values accordingly [13].

The Deep Learning model that we have trained from scratch is as shown in the Fig. 3. It consists of an *Image input layer* , *3 Convolution layers*, *3 Normalization layers*, *3 ReLu activation function layers*, *3 MaxPooling layers*, and finally the *Classification layer* which consists of *a fully connected flattening layer*- an array of neurons, *a softmax layer* which labels the output with some probabilities. All these layers combined together perform tasks like Feature Extraction, Normalizing the extracted features, max pooling the normalized features, train a fully connected neural network and finally classify them accordingly. A simple flowchart of the process is as shown in Fig. 4.

IV. Results and Discussion

In this study, we had trained a network from scratch on CXR images and classified them into COVID+VE and COVID-VE classes. We had tested on CXR images that were not used in the training phase, and got good results that were 95.63% accurate(overall). We had trained the model upto 1640 iterations which we found sufficient to validate the trustworthy of our results. Training accuracy indicates how correct the image being currently trained is classified under the correct label. The *loss function* calculated is actually *cross-entropy loss function* which is plotted for the same iterations. It tells how close is the validation image to the trained image. Usually training is stopped if the training parameters are not changing enough, but we had continued it till the final epoch so that we can see the end results.

Following Table I shows the number of COVID +ve images and -ve images used in the training.

TABLE I
Label Distribution

Label	Count
COVID+ve	516
COVID-ve	516

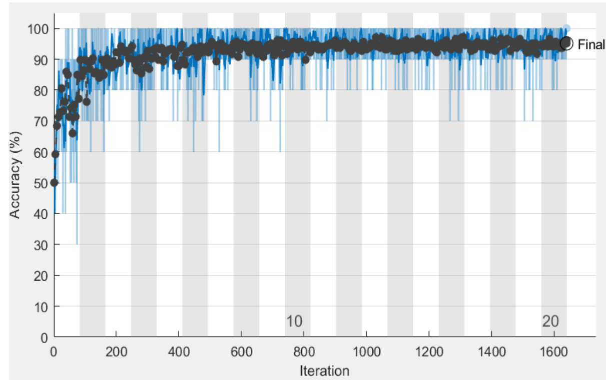
Also the training accuracy and loss were measured and tracked during the training process. It has been shown in the Fig. 5(a) and Fig. 5(b).

As we can see from the accuracy plots, training and validation plots go hand in hand, depicting good trained model which can classify accurately ($> 90\%$). Cross entropy loss depicts how good is the training progressing further, lower values are best. To measure the 'effectiveness' of the model, a *Confusion Matrix* is used [14]. Performance of the model, depends on how effectively and accurately it classifies the dataset. Confusion Matrix is a performance measurement for machine learning classification. Same has been plotted in Fig. 6. As we can see from the confusion matrix plot, majority of the images have been classified correctly (***true positive***) and few of them ($< 4\%$) have been wrongly classified (***false positive***).

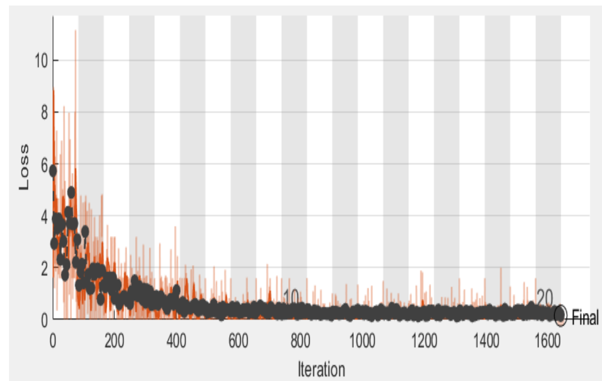
Further, we randomly selected CXR images from the test dataset, and tried to classify them based on the trained network. The results came out be 100% accurate. This shows that the network is responding well on the test images. Example classified images has been shown in the Fig. 7.

V. Conclusion and Future Work

Based on this study and various other sources, it can be concluded that deep learning with CNN has a significant role in the detection and classification of COVID-19 from CXR images. We had acheived the accuracy of about 95.63% which we find good in terms of proper classification. This model can accurately classify about 96.2% of the images into



(a)



(b)

Fig. 5. (a) Training and validation accuracy of the model and (b) cross entropy loss. The black dots(validation accuracy) closely match with the blue line(training accuracy) and the orange line(loss function)

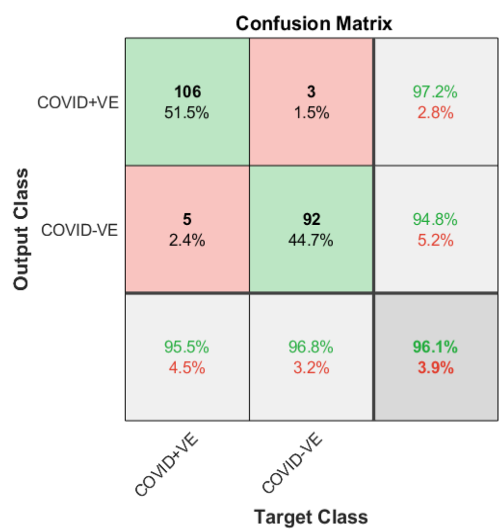


Fig. 6. Confusion Matrix. Green colored region depicts correctly classified data and orange colored region depicts wrongly classified data

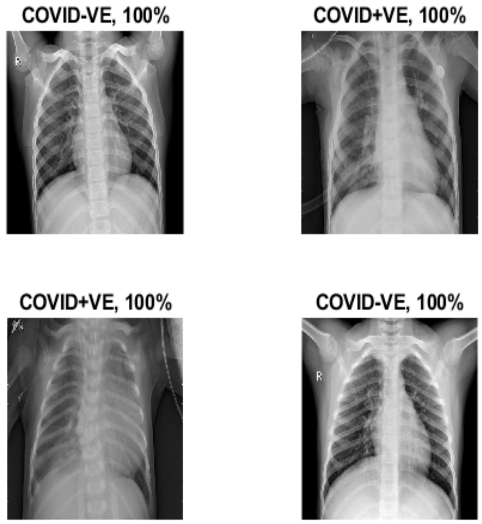


Fig. 7. Tested CXR images which turned out to be 100% accurately classified.

correct labels of data. Rest 3.8% of images have been wrongly classified. However, this can be improved using pretrained, more advanced CNNs like VGG16, ResNet50, InceptionV3, Inception ResNetV2, GoogleNet, etc. [15] [16]. These studies can help medical staffs in dealing such pandemics more safely. Since, medical treatments have a certain limits, we should utilise other measures as well which is some what non-medical. Radiographs can easily be done at various hospitals and medical centers. Processing the radiographs using the model we have defined in this study, can significantly improve the speed of detection of COVID-19.

In this era of Artificial Intelligence, Machine Learning, we must welcome such steps of automation which do not involve humans, as they can be erroneous. Future work may include building AI based apps that can detect the disease automaticlly on scanning the CXR images. Also, when plenty of data is available, we may further improve the detection accuracy. The model may be trained such that it could be used to classify different lung diseases as well like, SARS, Asthma, etc.

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