COVID Detection from Chest X-rays with DeepLearning: CheXNet

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***Abstract*— The novel corona virus is a rapidly spreading viral infection that has become a pandemic posing severe threats around the world. It is necessary to identify the cases priorly so that we can prevent the spread of this epidemic. But the availability of test kits is low which is main drawback. To overcome this AI is assistive and even used in COVID detection and prediction. A model for COVID prediction from chest X-rays using CheXNet is presented in this paper. This proposed model classifies the binary classes (COVID and normal) with 99.9% accuracy. CheXNet is a CNN model that used ChestXray14 dataset and was trained to detect abnormalities in chest X-rays. Generally, this model was extended to detect all the 14 pathologies in chestXray14 dataset. We used it's pre trained model Densenet121 in our model to detect COVID19 from binary classes.**

Keywords*— *COVID 19, CheXNet, DenseNet121, Pneumonia

I. Introduction

For the last eight months, we are witnessing pandemic situation throughout the world due to COVID 19, a new corona virus first observed in Wuhan, China in December ,2019 first suspected as pneumonia. Then after initial study, the virus is identified as its genesis I Severe Acute Respiratory Syndrome (SARS) and is termed as SARS-CoV-2. This virus causes respiratory infections like cold at an early stage and can lead to the most severe respiratory attacking diseases like Middle East and Severe Acute Respiratory Syndromes called MERS and SARS. The clinical features of the disease include fewer, sore throat, headache, cough, mild respiratory symptoms even leading to pneumonia. The testing techniques that are being currently used for COVID diagnosis are Polymerase Chain Reaction (PCR) and Reverse Transcription PCR popularly known as RT-PCR. As RT-PCR tests take much time for prediction, and also due to limited availability of these test kits, early detection cannot be done which in turn increases the spread of disease. COVID became a pandemic effecting globally and right now there is no vaccine available to cure this. In this epidemic situation Artificial Intelligence (AI) techniques are becoming vital.

Some of the applications where AI is imported are- AI is employed in cameras to trace infected patients with travel history using face recognition, robots to dis-patch food and medicines, drones to sanitize public places etc. [1]. Nowadays Artificial Intelligence is significantly being used to analyze RNA structure of COVID-19 virus and in research for discovering its drugs and vaccine. A vast research is being carried out in using AI in health care systems widely from disease prediction, patient monitoring, analyzing RNA structures, discovering new drugs and medicines for disease cure and developing vaccines for many diseases. Implementation of machine learning techniques for automatic disease diagnosis and identification is aiding the doctors as a supportive tool and gaining its popularity in the medical field as one of the major application areas of ML. Deep Learning (DL) a sub field of ML is being successfully applied in several issues like carcinoma detection, carcinoma classification, and respiratory disorder detection from chest x-ray pictures. Day by day the covi19 is growing at an exponential rate so, we need to inculcate these AI techniques to increase the testing rate. Recently, many researchers widely used radiology images for COVD-19 detection. The observation from the chest X-ray is a dis-criminating factor; if the chest X-ray is normal; patients can go home and wait for the laboratory test results, but in other case when using RT-PCR test the results are obtained late and the patient will be quarantined until the result arrives. That's where the significance of our work carried out in this paper lies. Thus, CT images and X-rays have vital role in prior detection of this disease which can be used as screening tool. Therefore, simple, precise, and faster AI models are helpful to overcome the problem of delay in disease identification and help patients in early discovery and cure. Deep Learning is used in such disease diagnosis, prediction and even treatment. In this paper, a deep learning model called CheXNet [6], that takes chest X-rays as input and gives the probability of predicting the COVID-19 as output is presented and acts like an aiding tool for pathology. This was trained to predict 14 different pathologies. Since, this model was already trained on chest X-rays during the development we can get better and accurate results of prediction using this. So, to increase the COVID testing rate we can use X-ray test as preliminary test and if AI prediction test results in positive then patient can undergo medical test.

II. Related Work

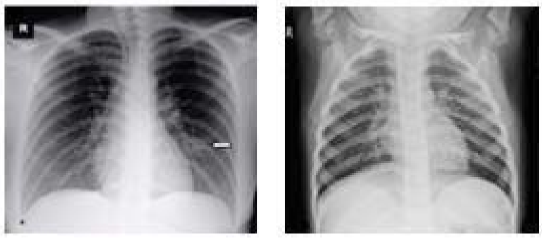
This section briefs some of the recent works done on COVID prediction using chest X-rays, different models that are used in prediction and also some works related to AI and deep learning in disease prediction, diagnosis. From the initially days of COVID outbreak only many researchers started working on this and discovered many methods for COVID prediction and cure.

The ideology of using x-ray images in prediction of COVID-19 came from the initial approaches which are used in detection of pneumonia from chest X-rays using deep neural networks [2]. The authors used CNN in prediction of pneumonia from chest X-rays. They developed CNN model that takes chest X-rays and outputs pneumonia prediction. Transfer Learning is a technique where we train a model on one problem and use it on other related problem. There are also previous works done on COVID prediction using transfer learning [3]. Apostol Poulos et al., have an X-ray dataset taken from patients with microorganism respiratory disorder, confirmed COVID-19 cases, and normal diseases from public repositories for the automated detection of the Coronavirus. They used transfer learning with CNN, yielding outstanding results approximately 96%. In this three distinct CNN based models ResNet50, InceptionV3 and Inception-ResNetV2 have been proposed for the identification of COVID, pneumonia infected patient using chest X-ray radiographs by Ali Narin, Ceren, Pamuk [4]. They performed these models with 98%, 97% and 87% accuracies respectively. In [5] the authors used darknet model and implemented 17 convolution layers, introducing different filtering on each layer. They also mentioned the findings that are often noticed in X-rays of corona infected patients as Groundglass opacities (GGO), A crazy paving appearance, Air space consolidation, Broncho vascular thickening, Traction bronchiectasis. In [6], the authors developed a CheXNet model that detects Pneumonia from chest X-rays that works much more accurate than a well practicing radiologist. They have evaluated the model's performance using F1 measure and shown that the model's performance was much better than the experienced practitioners. The model was enhanced to identify all 14 diseases of Pneumonia category from chestX-ray14 dataset and achieved acknowledgeable and satisfactory results for all those disease predictions. Hence, using CheXNet for COVID-19 prediction is reasonable and for training this model we need a chest X-ray of chest x-ray images and are available also on internet [7].

III. Materials and Methods

A. X-ray image dataset

The dataset to be considered should contain only chest X-rays. There are various open access sources available on internet [7]. The dataset we considered for implementing this model, consists of 1824 images of chest X-rays of equalized COVID and non-COVID classes i.e. 912 confirmed COVID-19 X-rays and 912 non-COVIDX-rays [8]. The dataset is splitted into two sets training set and test set in 8:2 ratio. The following Fig. 1(a) shows sample chest X-ray of a non-COVID patient and Fig. 2(b) shows X-ray of a COVID-19 infected person.



(a) (b)

Fig. 1. Sample x-ray of (a) non-COVID patient
(b) COVID infected person

The distinct observations can be made from X-ray images of COVID-19 infected particularly in the lower lobe areas, and in the posterior segments, with distribution in peripherals and subpleural distribution. These observations are also observable in both the lungs even in the early stages of virus infection.

The images of the dataset are first downscaled to 224 X 224 and are normalized. We have augmented the training data by performing horizontalflipping, zooming, rotating and rescaling etc. The original cheXNet model used a dataset called chestX-ray14 which is the present largest available dataset of chest X-rays. Wang et al. (2017) [9] developed the ChestX-ray14 dataset and it consists of 1,12,120 X-ray images of 30,805 patients and each x-ray image is labeled with14 distinct respiratory diseases.

B. Proposed Model

CheXNet:

CheXNet is a deep Convolutional Neural Network consisting of 121 layers which is shown in Fig. 2. This network produces a heatmap that localizes the areas in which disease symptoms are highly indicative in the image along with the prediction probability. Figure below shows the architecture of CheXNet model that includes all convolution layers and the fully connected layers.

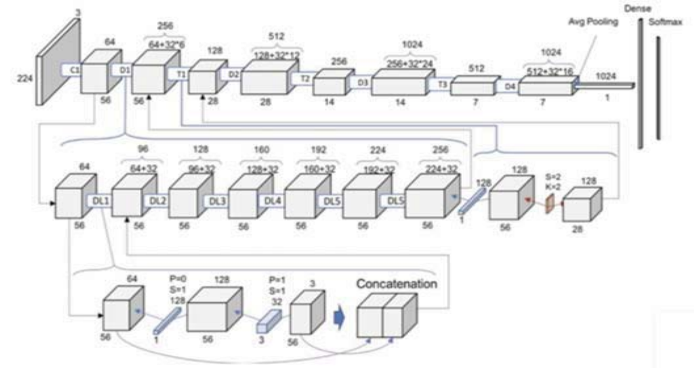


Fig. 2 Architecture of CheXNet model.

This was developed to predict the pneumonia from chest X-rays. This model used chestX-ray14 dataset containing X-rays of 14 different pathologies. Four practicing radiologists classified the images in the test set, on which the performance of the model is compared to that of radiologists. CheXNet was primarily developed for pneumonia prediction. They optimized the weighted binary cross entropy loss as

$$L(X,y) = -w_{+}.y\log P(Y=1|X) \\ -w_{-}.(1-y)\log P(Y=0|X) \quad (1)$$

where P (Y = 1|X) is the probability that the model assigns the label to the image as COVID and P (Y = 0|X) is the probability that the model assigns the label to the image as non-COVID. W_{+} is the ratio of number of negative cases to the total number of positives and negative cases of COVID. W_{-} is the ratio of number of positive cases to the total number of positives and negatives cases of COVID. The implementation of this model is shown in Fig.3. [5].

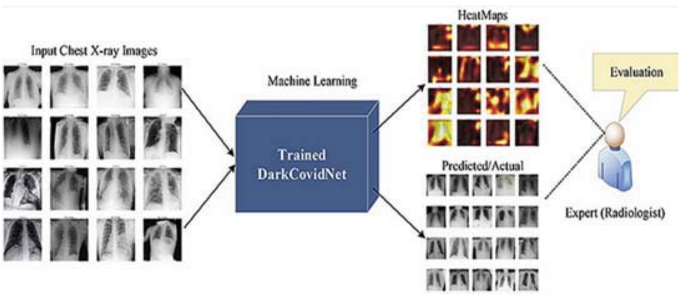


Fig. 3 Implementation of CheXNet model.

Implementation:

For our model, we build a CheXNet model by using pre-trained model of DenseNet121. It has five convolutional layers and average pooling is used. We used the weights of the pre-trained model taking the weights file and loaded those weights in our model. We achieved more accuracy compared to the models which used transfer learning cause this CheXNet model was trained on chest x-ray images itself unlike other models. Fig. 4. shows the used model summary depicting the working of model.

```
Model: "functional_1"
________________________________________________________________
Layer (type)     Output Shape          Param #     Connected to
================================================================
============================
input_1 (Input Layer)          [(None, 224, 224, 3) 0
________________________________________________________________
zero_padding2d (ZeroPadding2D) (None, 230, 230, 3)  0
input_1[0][0]
________________________________________________________________
conv1/conv (Conv2D)           (None, 112, 112, 64) 9408
zero_padding2d[0][0]
________________________________________________________________
conv1/bn (BatchNormalization)    (None, 112, 112, 64) 256
conv1/conv[0][0]
________________________________________________________________

zero_padding2d_1 (ZeroPadding2D (None, 114, 114, 64) 0
conv1/relu[0][0]
________________________________________________________________
conv2_block6_2_conv (Conv2D)     (None, 56, 56, 32)    36864
conv2_block6_1_relu[0][0]
________________________________________________________________
conv3_block12_2_conv (Conv2D)    (None, 28, 28, 32)    36864
conv3_block12_1_relu[0][0]
________________________________________________________________
conv4_block24_1_conv (Conv2D)    (None, 14, 14, 128) 126976
conv4_block24_0_relu[0][0]
conv4_block24_1_bn (BatchNormal (None, 14, 14, 128)   512
conv4_block24_1_conv[0][0]
________________________________________________________________
conv5_block16_2_conv (Conv2D)    (None, 7, 7, 32)      36864
conv5_block16_1_relu[0][0]

conv5_block16_concat (Concatena (None, 7, 7, 1024)    0
conv5_block15_concat[0][0]
conv5_block16_2_conv[0][0]
bn (BatchNormalization)          (None, 7, 7, 1024)    4096
conv5_block16_concat[0][0]
________________________________________________________________
relu (Activation)                (None, 7, 7, 1024)    0
bn[0][0]
________________________________________________________________
avg_pool (GlobalAveragePooling2 (None, 1024)           0
relu[0][0]
________________________________________________________________
dense (Dense)                    (None, 2)             2050
avg_pool[0][0]
================================================================
============================
Total params: 7,039,554
Trainable params: 2,050
Non-trainable params: 7,037,504
```

Fig. 4. Important convolution layers and model parameters

Algorithm:

- First, we load the dataset that contains 1824 images with 2 classes (COVID 19 and normal X-rays) for binary classification.
- As the DenseNet121 takes input images of size 224 x 224, resize the images in our dataset to 224 x 224.
- Take the DenseNet121 network with pre-trained weights of CheXNet without including the fully connected (FC)layer as head.
- Then freeze the CONV weights of DenseNet121 such that only head network will be trained.

- Finally, construct a new fully-connected layer consisting of POOL => FC =SIGMOID layers and append to top of DenseNet121.
- Now, pass a new X-ray image to detect whether the patient is having COVID-19 or not.

The model is built with five conv layers and is trained with pre-trained weights. The summary of the model implemented is shown in below figure Fig.3.2.2 in which we represented only significant layers and parameters. We also visualized feature maps in our CheXNet model to observe how the given input chest x-ray is considered by each layer of the proposed CheXNet model. This gives insights about the internal representation of how the model considers input and its evaluation. This feature maps or activations maps provide the preferential regions of the image that are used by convolutional neural networks to classify covid chest x-ray with that of normal one. Below figures Fig.5 and Fig.6represents the activation maps of last blocks in different CONV layers of our model for both covid patient and normal patient x-rays. From those we can clearly observe the difference and evaluation process of CONV layers. The differences in activation maps of both depict that covid x-ray contains major portion of area affected when compared to that of normal one. Finally, by these the model can clearly classify the chest x-rays into respective
classes.

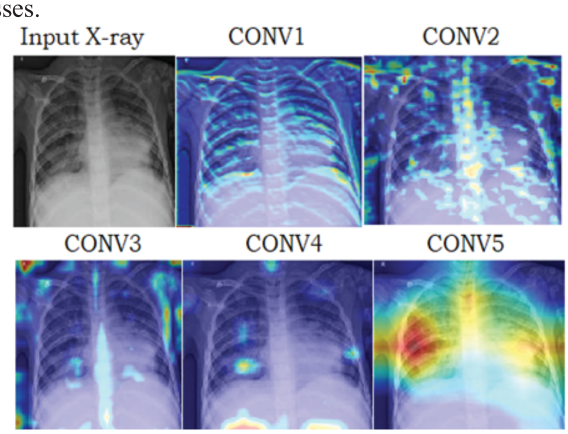


Fig.5 Activation maps depicting discriminative areas of covid patient chest x-ray obtained after end of each CONV layer of our CheXNet model

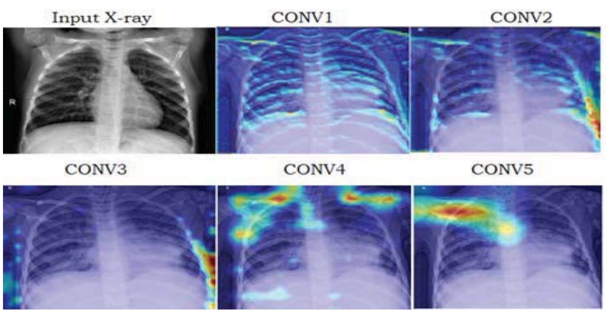


Fig.6 Activation maps depicting discriminative areas of normal patient chest x-ray obtained after end of each CONV layer of our CheXNet model.

C. Results

We performed our experiment to predict COVID19 from chest x-ray images. By training our developed DenseNet121 model on 1824 images we achieved excellent results showing that our model can predict with 99.9% accuracy. The high efficiency i.e accuracy of this model is obtained because of the datset considered -as it clearly depicted the distinguishing and another reason is that we considered the weights of pre-defined model which are already trained on chest X-rays. Thus, we can use this in real time scenarios of COVID detection in screening tests with any further developments needed.

Performance Metrics:

In a model the values like accuracy, precision, recall, f1-score are considered as performance metrics since they are used to evaluate the model performance.

Accuracy: It is the measure of total number of predictions that are perfectly classified.

Precision: It is the measure of specific cases expected based on confidence.

Recall: It can be defined as ratio of the number of images classified as positive to the total number of existing relevant positive images, which is similar to true positive rate.

F1-score: It is the weighted average of precision and recall. Fig.7 shows the performance of our model.

	precision	recall	f1-score	support
COVID-19	1.00	1.00	1.00	173
Non-COVID-19	1.00	1.00	1.00	192
accuracy			1.00	365
macro avg	1.00	1.00	1.00	365
weighted avg	1.00	1.00	1.00	365

(365,)

Fig. 7(a). Performance metric values obtained for our model.

```
[[173   0]
 [  0 192]]
acc: 1.0000
sensitivity: 1.0000
specificity: 1.0000
```

Fig. 7(b). Confusion Matrix

We used sigmoid activation for the output layer and in compiling Adam optimizer is used and binary cross entropy is considered as the loss function.

It ends up with an accuracy of 99.9% and values of sensitivity and specificity as 1.0000 and 1.0000 respectively with the parameter values as epochs 10, batch size 5, learning rate 1e-3, test size 0.2.

Below graph Fig.8 shows variation in different measures of accuracy and both training loss and validation loss.

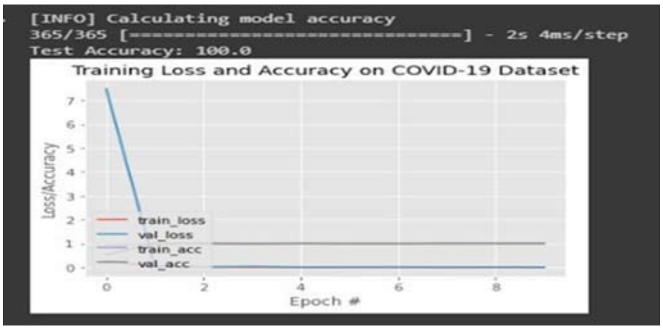


Fig. 8 Training and Validation(test) accuracy and loss curves.

IV. CONCLUSION

In this paper we used CheXNet model using chest x-ray images to predict the novel COVID-19 disease. This idea can be implemented in real-time scenarios of COVID-19 detection with further developments.

Our main future goal is to increase the dataset size so that we can train the model still better for accurate predictions because, in machine learning training with more data makes the model to perform much better on unseen data. This can also be further developed to predict the possibility of that affected person to survive. We are also working on this. However, it is our hope that this project will continue to improve and potentially offer insight that will contribute toward medical research regarding COVID-19.

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