Deep Learning based Diagnosis Recommendation for COVID-19 using Chest X-Rays Images

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Abstract- **A novel coronavirus spillover event has emerged as a pandemic affecting public health globally. Screening of large numbers of individuals is the need of the hour to curb the spread of disease in the community. Real- time PCR is a standard diagnostic tool being used for pathological testing. But the increasing number of false test results has opened the path for exploration of alternative testing tools. Chest X-Rays of COVID-19 patients have proved to be an important alternative indicator in COVID-19 screening. But again, accuracy depends upon radiological expertise. A diagnosis recommender system that can assist the doctor to examine the lung images of the patients will reduce the diagnostic burden of the doctor. Deep Learning techniques specifically Convolutional Neural Networks (CNN) have proven successful in medical imaging classification. Four different deep CNN architectures were investigated on images of chest X-Rays for diagnosis of COVID-19. These models have been pre-trained on the ImageNet database thereby reducing the need for large training sets as they have pre-trained weights. It was observed that CNN based architectures have the potential for diagnosis of COVID-19 disease.**

Keywords- COVID-19, CNN, Deep Learning, Convolutional Neural Network, Diagnosis Recommender, ImageNet

I. INTRODUCTION

The outbreak of coronavirus disease in December 2019 in China spread rapidly across all parts of the world by January 2020. The World Health Organization (WHO) termed it as COVID-19 and declared it a pandemic on January 30, 2020 [1]. Till June 8th, 2020, the number of confirmed cases is around 7 million globally, and the global fatality rate is around 3-4%.

Since it is a highly contagious disease and is spreading rapidly, governments of almost all of the affected countries are taking it on priority to isolate infected individuals as early as possible. The general symptoms of COVID-19 patients are flu-like such as fever, cough, dyspnea, breathing problem, and viral pneumonia. But these symptoms alone are not significant. There are many cases where individuals are asymptomatic but their chest CT scan and the pathogenic test were COVID-19 positive [2]. So, along with symptoms, positive pathogenic testing and positive CT images/X-Rays of the chest are being used to diagnose the disease. For pathological testing, Real- time PCR is being used as a standard diagnostic tool [2].

Healthcare systems around the world are attempting to expand testing facilities for COVID-19. More and more testing will lead to the identification and isolation of infected persons, thereby reducing the spread among the community [3]. But availability does not ensure reliability. The major concern for the governments at this stage is the false negative test results – the test results are negative for the infected individual [3]. Such individuals may unknowingly transmit the virus to others. False test results thus have a negative effect on the efforts to curb the spread of the virus. The impact of this concern on the safety of public and health workers can't be determined as there are no clear or consistent reports on these test performance characteristics. The sensitivity of these tests is largely unknown [3].

In this scenario, Chest X-Rays of COVID-19 patients have proved to be an important alternative tool for COVID-19 diagnosis due to its high sensitivity [4], [5]. But the accuracy of diagnosis using X-Rays strongly depends on radiological expertise. And it becomes a tedious task when the number of patients is large. A diagnosis recommender system that can assist the doctor to examine the lung images of the patients will reduce the diagnostic burden of the doctor.

Deep Learning techniques are artificial neural networks in which each layer has multiple neurons that function similarly to the neurons of the human body. Convolutional neural networks (CNNs) are one of the deep learning techniques that have proven to be successful and effective in the field of medical imaging classification. There have been several studies that have used CNN to diagnose pneumonia and other diseases based on radiography. CNN based architecture has been proposed in [6] to identify different lung diseases. In [7], the Chest X-Ray dataset consisting of around 100,000 X-ray images was used to train a CNN model for the diagnosis of 14 diseases. CNN has also been used for predicting pneumonia [7], [8]. A recommendation system has been proposed in [9] that helps radiologists to identify infected areas in CT images.

Hence CNN becomes a natural candidate for diagnosis recommendation of COVID-19 patients. In[10], [11], seven different existing deep learning neural network architectures were compared using small data sets consisting of only 50 images. Out of 50 samples, 25 were of COVID-19 positive and 25 from COVID-19 negative patients.

Some researchers have proposed new architectures of CNN [8], [12]–[14], or fine-tuned ResNet50 [15], [16] for the problem of classifying Chest X-Rays. But they still are in the preprint stage.

II. ARCHITECTURES

A pre-trained model is a model created by someone else to solve a particular problem and can be used by anyone to solve a similar problem. Several image classification CNN models pre-trained on image datasets are available. The ImageNet is a large-scale, accurate, and diverse image database. The images in this database are arranged as per the WordNet hierarchy[17]. There are approximately 100,000 phrases in WordNet each having around 1000 images on average. For this study, architectures of the following four models pre-trained on Image Dataset have been used:

- **Inception V3:** Szegedy et al[18] proposed the Inception architecture in 2014. The original architecture was called GoogleLeNet. All the subsequent versions were called Inception Vn (n is the version number). Batch Normalization was added in Inception V2 as an improvement over Inception V1. In InceptionV3 model factorization methods were introduced as an improvement over V2.
- **ResNet50:** In 2015 He et al [19] proposed ResNet - The Residual Networks architecture. It has 50 convolutional layers with skip connections that help in improving the learning accuracy of the model. Also, it uses global averaging pooling instead of fully connected layers thereby reducing the model size.
- **MobileNet:** In 2017 another CNN architecture called MobileNet was proposed by Howard et al [20]. In this separable convolution have been arranged depth-wise and they apply the convolution operation on each color channel separately instead of taking them as a whole. The cost of computation gets reduced in this architecture.
- **Xception:** François Chollet developed Xception in 2017 [21]. This model can be considered as an improvised version of Inception as modules of Inception have been replaced with depthwise separable convolutions. This latest and accurate model scores upon speed and accuracy.

III. EXPERIMENT

A. Datasets

A total of 6249 Chest X-Ray images were collected from public databases available on various GitHub repositories [22]. Among these, 320 were of COVID-19 positive patients and 5928 were of patients who did not have the virus. Images were classified as COVID-19 and Non-COVID-19. Some samples of images belonging to the classes COVID-19 and Non-COVID-19 have been shown in figure 1 and figure 2 respectively.

The ratio used to divide the dataset into training and testing sets was kept at 75:25. For training 4686 records were used and 1563 were used for testing. The validation set is kept as 30% of the training set.

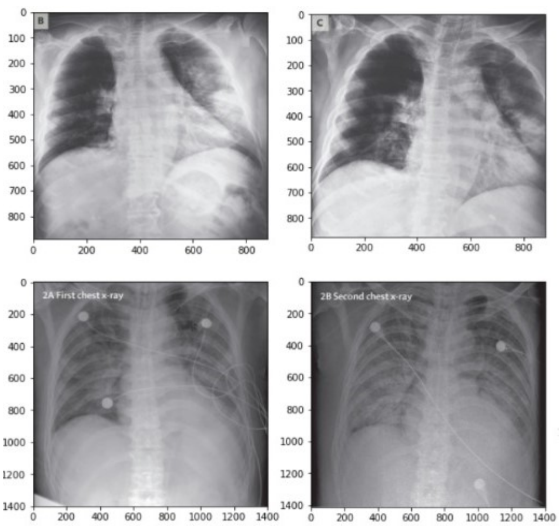

Fig. 1 Sample images of Chest X-Rays of COVID-19 patients

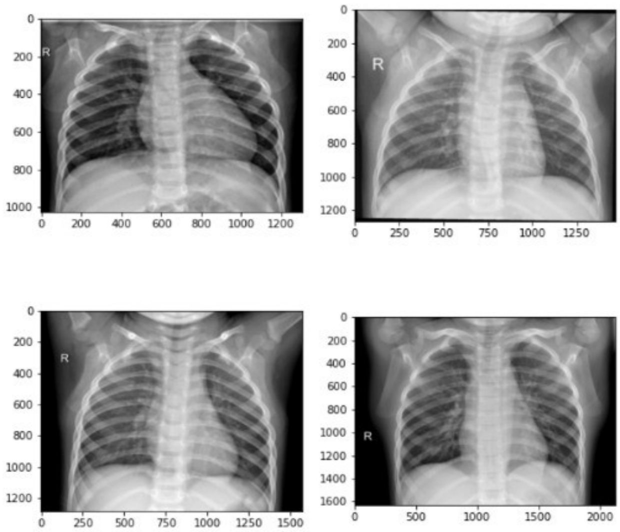

Fig. 2 Sample Images of Chest X-Rays of Non-COVID-19 Patients

B. Experimental Setup

For the implementation of these four architectures (namely Xception, ResNet50, MobileNet, and Inception V3) Keras framework with TensorFlow as the backend was used. Keras provides pre-trained weights from the ImageNet database on these pre-trained models. Though the images in the ImageNet dataset on which these models are trained may not be similar to images collected for study but may help by transferring knowledge learned to make the intended task more efficient. Also, pre-trained weights reduce the requirement of a large volume of data for training.

Online Jupyter Notebook based service Collaboratory by Google Research was used to execute the Python code. The Tesla P4 GPU was used for faster processing which is provided by Collaboratory. Adadelta Optimizer was used to train all the networks and Mean Squared Error was used as the loss function. For training, the batch size was set to 32 and the number of epochs was set to 200.

IV. RESULT

Fig 3 to Fig 6 are the confusion matrices observed on the testing dataset for all four models i.e., Xception, Resnet50, MobileNet, and InceptionV3. The results of these four models have been summarized in Table 1. The performance of all of the models has been measured on parameters like accuracy, specificity, precision, recall/sensitivity, and F1 score.

Accuracy values of four models indicate that the CNN architectures are dependable for the diagnosis of COVID-19 disease. Out of all the four models, MobileNet turns out to be best with the maximum F1 score. The specificity that defines the ability of the model to avoid false alarms is more than 99% in all models. But Recall/Sensitivity that defines the ability of a model to detect positive cases is found to be good in Mobilenet and Inception V3 only. Although the Xception model is quite close to Mobilenet but due to low sensitivity of 0.6, it cannot be considered as a robust model.

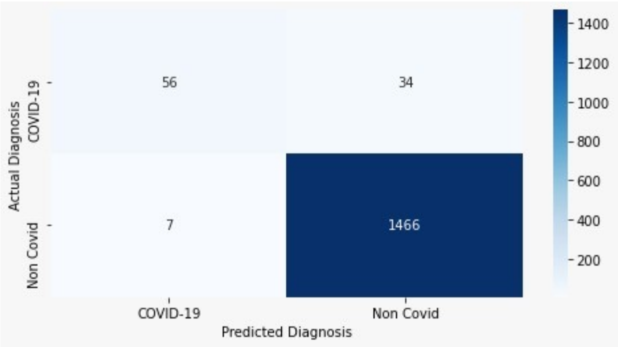

Fig 3 Confusion Matrix for Xception Model

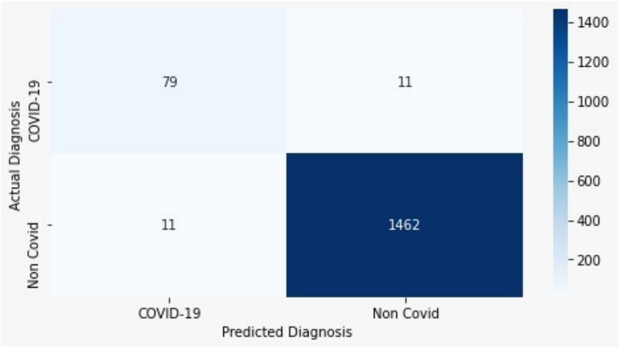

Fig 4 Confusion Matrix for MobileNet Model

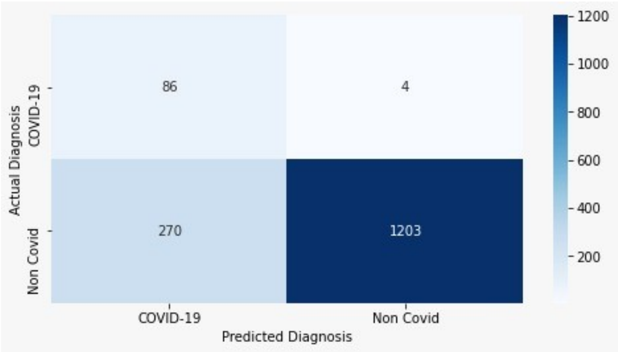

Fig 5 Confusion Matrix for ResNet50 Model

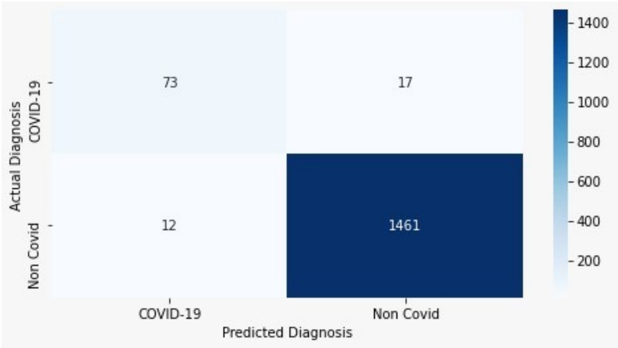

Fig 6 Confusion Matrix for Inception V3 Model

Table 1 Classification results of four architectures

Method	Evaluation Metrics								
	TP	**TN**	**FP**	**FN**	**Accuracy**	**Specificity**	**Precision**	**Recall/Sensitivity**	**F1 Score**
Inception V3	73	1461	12	17	0.981	0.992	0.859	0.811	0.834
ResNet50	86	1203	4	270	0.825	0.997	0.956	0.242	0.386
MobileNet	79	1462	11	11	0.986	0.993	0.878	0.878	0.878
Xception	56	1466	7	34	0.974	0.995	0.889	0.622	0.732

V. CONCLUSION

COVID-19 is affecting the health of the global population at an alarming rate. Testing of large numbers of individuals is crucial to curb the spread of disease. Real-time PCR is a gold standard pathological test for the diagnosis of this disease. But the increasing number of negative false reporting has led to the use of Chest XRays as an alternative for diagnosis of COVID-19. Deep learning-based recommender systems can be of great help in this scenario when the volume of patients is very high and required radiological expertise is low. In this study, four different deep CNN architectures were investigated on images of chest X-Rays for diagnosis recommendation of COVID-19 patients. These models, pre-trained on ImageNet database, have pre-trained weights that help to transfer their prior knowledge on the dataset being investigated. Mobilenet model turns out to be the best out of all the models.

The results suggest that CNN based architectures have the potential for the correct diagnosis of COVID-19 disease. Transfer learning plays a major role in improving the accuracy of detection. Fine-tuning of these models may further improve the accuracy. Other pre-trained models may also be explored for building a recommender diagnosis system. Future work may include developing new architectures based on CNN for the detection of COVID-19 as well as other diseases in the medical domain.

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