COVID-19 Detection using Convolutional Neural Network Architectures based upon Chest X-rays Images

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Abstract—The novel Coronavirus has really been the unexpected Catastrophe, which no one could have even thought of. It has emerged as a pandemic and has raised questions on the health infrastructure and facilities available as it is required to get a large number of people tested. RT-PCR is the standard diagnostic test being used. But there are several issues with RT-PCR testing like relying only on one approach even when it is getting difficult for most countries to procure the required amount of testing kits, also there have been some cases of false positive results. All these factors definitely call for a search of alternative testing methodologies, so it not regired to rely on just one approach. Apart from RT-PCR testing, Chest X-rays can be a great tool to know about the status and severity of COVID-19. Once obtaining the chest X-rays of a person a call has to be made on the COVID-19 status and that needs very high accuracy and expertise and again there will be a shortage of the expertise. So, a solution has been proposed to this problem by developing a COVID-19 detection system, which can assist the medical experts regarding the report and then the experts can make a final call. As observed, Deep Learning techniques, especially Convolutional Neural Network (CNN) have proven to be outstanding in medical image classification and analysis, and as our task is similar to medical image classification, CNN is a good choice for our use case. So, we analyzed four different CNN architectures on Chest X-ray for Covid-19 Diagnosis. The models used are pretrained on ImageNet datasets. Transfer Learning has been used to generate results. A comparative study of the results obtained with different architecture reveals that structures based on CNN have great potential for Covid-19 diagnosis and detection.

Keywords—RT-PCR; COVID-19; CNN; Chest X-ray; ImageNet

I. INTRODUCTION

Coronavirus outbreak took place in December 2019 in some regions of China, but soon several other countries started reporting covid-19 cases and it was then identified and declared as COVID-19 Pandemic by the World Health Organization on January 30,2020 [1]. Till February 2021, the global case count has crossed 50M mark and more than 2M lives have been lost.

As, this disease spreads from human to human and is highly contagious, people have been advised to wear masks and maintain social distancing. Also, the infected/suspected individuals are asked to isolate themselves so that they do not act as carriers for others. Common symptoms are cough, fever, breathing problems, pneumonia, loss of smell and taste. But these are not necessary symptoms for a patient to be Covid-19 positive. There are significant number of asymptomatic people who don't face any such issues, but their tests have revealed that they are COVID-19 positive [2].

Symptoms alone are insufficient to diagnose COVID-19 and the support of medical diagnostic tests like RT-PCR, Chest X-ray are required but the healthcare facilities around the whole world is facing severe challenges to facilitate testing for more and more people, so that their isolation can be done properly. But the supply of medical tests like RT-PCR is limited and demand is growing, which leads to large number of populations remaining untested and even accuracy can be compromised in such tense environments [3].

The untested positive individuals pose serious threat to others and this nature of disease is the sole reason of the exponential growth in the cases with time. A single infected person can infect a large chunk of people who come in close vicinity with him.

In such a situation, there is an urgent need of alternative testing methodologies so that more population can have access to getting tested. Amongst all the diagnostic tools and tests, it has been found out that, Chest X-ray reports are an important diagnostic and detection tool due to its high sensitivity [4], [5],[6]. But it is also required to acknowledge the fact that, medical expertise is of utmost importance here and to give a verdict on the covid status of a patient by looking at the Chest X-Ray report is a difficult task that too with ever growing number of patients. Also, medical experts will definitely need some assistance in the decision-making process.

CNN can help in the above-mentioned issue by helping medical experts make an opinion. Convolutional Neural Networks (CNNs) is the deep learning technique that has shown great promise with regard to medical image analysis. These are artificial neural networks in which each layer has multiple neurons and several different architectures can be built by changing the number of layers, number of neurons in different layers and these models can perform very differently from each other. With CNN based architectures being used with respect to lung diseases and pneumonia [7] and a diagnosis recommender system being proposed in [10].

In [8], which uses a Chest X-ray dataset in which 100000 images in total were taken for training the model and diagnosis of 14 different diseases was done.

So, CNN definitely shows up to be a promising candidate for the recommendation. In [11],[12] different deep learning models were compared using smaller datasets.

Our work is novel in the sense that, a completely balanced dataset has been used to eliminate biases towards any one class in our prediction, and as a result we obtain better performance than the ones trained on imbalanced datasets. Also, a three-class classification has been performed to classify the covid-19, pneumonia and a normal person.

Active researchers in this area have also proposed several new different architectures of CNN [9], [13]– [15] or several tweaked ResNet50 [16], [17] for classification of Chest X-rays.

II. ARCHITECTURES

Architecture includes different arrangement of various layers like convolution layers of varying kernel size and filter numbers, fully connected layers, pooling layer or dropout layers. For this, technique called transfer learning is used. In transfer learning pre-trained model are used. Pre-trained models are models which are trained on one dataset but can also be used for processing other dataset of similar nature. These models can be little tweaked as per the need, but the core of the model remains the same. The proposed model for COVID detection is shown in figure 1. For this study, following four models are used which are originally trained on ImageNet dataset which is a large dataset of about 14 million images of about 1000 different classes [18]:

• Inception V3: Inceptionv3 is a convolutional neural network (CNN) which is used in image analysis and object detection and initiated as a module for GoogleNet [19]. It was originally introduced during the recognition Challenge on ImageNet dataset. The original name was derived from a very popular internet meme we need to go deeper, quoting a phrase from Inception film of Christopher Nolan.

 Pneumonia X-ray
 Image: Covid X-ray
 Image: Covid X-ray
 Image: Covid X-ray

 Pneumonia X-ray
 Image: Covid X-ray
 Image: Covid X-ray
 Image: Covid X-ray

 Image: CNN Layers
 Class
 Probabilities
 Actual Labels

 Image: Dense Layers
 Inference Layers
 Image: Covid X-ray
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 Image: Dense Layers
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Fig 1. Proposed model for Covid detection

It is CNN based model having total of 159 layers. In total it has 23,851,784 parameters, and its size is around 92 Megabyte. It is an improvement over Inception V2 by adding factorization method, which in turn is an improvement over Inception V1 by adding batch normalization method.

- MobileNet: MobileNet is an architecture that uses some special technique called depth wise separable convolution to deep and lightweight convolution neural network and gives an efficient model for computer vision applications. Its structure is mainly constructed on depth wise separable filters [20]. It is CNN based model having total of 88 layers. In total it has 4,253,864 parameters, and its size is around 16 megabyte which is very less as compared to another classification models available. Due to its reduced size, it is very computation efficient
- Xception: Xception Model is proposed by Francois Chollet, who is software engineer at Google Inc. In Xception architecture standard Inception modules are changed with depthwise Separable Convolutions [21]. It is CNN based model having total of 126 layers. In total it has 22,910,480 parameters, and its size is around 88 megabyte which is comparable with other present models.
- **DenseNet 121:** The core idea of DenseNet 121 is to modify the standard Convolution Neural Network layers. In standard CNN each layer is connected to the next layer [22]. For L layers, there are L direct connection - one connection between 2 consecutive layers. But in DenseNet each layer is connected to every other layer in the architecture, which form a Dense structure, hence its name is DenseNet. For L layers in the architecture, there are total L*(L+1)/2 connections. This is the core idea behind DenseNet which makes it extremely powerful.

III. EXPERIMENT

A. Datasets

Sample images from classes COVID, Normal and Pneumonia are shown in figure 2, figure 3 and figure 4 respectively.



Fig 2. Sample Chest X Ray images of Covid patients.



Fig 3. Sample Chest X Ray images of Normal person

Since there is no proper dataset available, which was required for this study. Hence, dataset was prepared by merging 3 opensource dataset available on Kaggle and GitHub [23].

The dataset consists of X-Ray images of 3 classes

- 1. Normal Person X-Ray
- 2. COVID-19 Positive Patient's X-Ray
- 3. Lung Pneumonia Patient's X-Ray

Also, dataset available on the above stated platforms are in varying quantity (COVID-19 X-Ray being the limiting factor). So, to prevent any biasing in the dataset to reduce any anomaly in training and testing dataset is trimmed down.

So, in the dataset there are 460 images of COVID-19, 460 of Normal and 460 of Pneumonia patient. Total training dataset images are 1380 (460 + 460 + 460).

For training there are 116 images of COVID-19, 116 images of Normal and 116 images of Pneumonia patients. Total testing dataset images are 348 (116 + 116 + 116).

Total images in this dataset are 1728 (1380 + 348). Approximately we have done 80-20 split for training and testing.

B. Experimental Setup

For implementation Keras is used. Keras is a python library which helps to import built in models and neural networks It also helps to create neural networks without much difficulty and is very important tool.



Fig 5. Confusion Matrix for DenseNet 121



Fig 4. Sample Chest X Ray images of Pneumonia patients

For model implementation Google Colaboratory is used. Colaboratory provides a free environment to developers to create and use Jupyter notebook which is entirely free up to certain ram and memory and runs within cloud in this one will write code same as Jupyter notebook and can save the file either in drive or remotely and can also share their work with other. Mini Batch gradient descent technique was used. Batch size is of 200 images. Steps per epoch comes out to be approximately 7. 10 epochs were used for training.

Also, one dropout layer with 0.5 rate is used to prevent overfitting over training dataset. Loss function used is categorical cross entropy which is a standard one and optimizer used is Adam optimizer.

IV. RESULT

Fig 5 to 8 shows the confusion matrix of the result derived after running the four models namely Inception V3, MobileNet, Xception, DenseNet 121 on the testing dataset. Table 1 to 4 shows the class wise recall, precision and F1-score of the result obtained after running the four models on testing dataset.

From confusion matrix of all the four models, MobileNet predicted the maximum number of correct outputs which is 331 whereas Xception shows 317, the least correct outputs, with 324 and 318 for Inception V3 and DenseNet 121 respectively.



Fig 6. Confusion Matrix for Incetption V3

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Fig 7. Confusion Matrix for Xception

From the tables presented, Precision which is the fraction of true positive divided by total number of true positive and false positive. For COVID-19 is maximum for Inception V3, Xception and MobileNet with value 1.0000, for Normal also Inception V3 achieved the highest score that is 0.9137 and for Pneumonia DenseNet comes out to be the superior one with score of 1.0000.

Similarly recall is the fraction of true positive divided by total number of true positive and false negative. For COVID-19 and Normal recall is maximum for MobileNet and DenseNet121 with value 0.9827 and 0.9913 respectively and for Pneumonia it is maximum for Inception V3 with a score of 0.9224. F1-score which is the combination of precision and recall is maximum for MobileNet for all the 3 classes namely COVID-19, Normal and Pneumonia with values 0.9913, 0.9987 and 0.9230 respectively. Therefore, MobileNet seems to be a promising option from all.

V. CONCLUSION

As COVID-19 has affected lives of the people of whole world, it is important for us to increase the testing as it is the only way to tackle COVID-19. As Real Time - PCR is the only gold standard test, but dependency on only one test alone is insufficient. In our study, we have considered 4 different

Table 1. Metrices of InceptionV3

	COVID-19	NORMAL	PNEUMONIA
Precision	1.0000	0.9137	0.8842
Recall	0.9568	0.9137	0.9224
F1-Score	0.9779	0.9137	0.9029

0.9987

0.9230

Table 2. N

0.9913

Precision Recall

F1-Score

	0.9568	0.9137	0.9224	Recall	0.9568	0.9655	0.8103
	0.9779	0.9137	0.9029	F1-Score	0.9779	0.8853	0.8703
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ietrices of widdhenet			1 able 4. Metrices of DenseNet				
	COVID-19	NORMAL	PNEUMONIA		COVID-19	NORMAL	PNEUMONIA
	1 0000	0.8014	0.9714				
	1.0000	0.0914	0.9714	Precision	0.9913	0.7986	1.0000
	0.9827	0.9913	0.8793	Recall	0.9827	0.9913	0.7672

F1-Score

0.9870



Fig 8. Confusion Matrix for MobileNet

CNN based architecture which are originally trained on ImageNet dataset and used the transfer learning technique for transferring the weights.

From the results presented above it clear that MobileNet is the best possible option and also all the 4 models didn't suffer from any kind of overfitting and underfitting. Also, our dataset is neutral with equal images in training and testing of all the three classes.

So, CNN based architectures provide a potential method for alternative testing methodology and help in tackling COVID-19 in the long run. In future as the flow of input data increases, we can further fine tune these models to get even better results, also different CNN architectures can be developed for detection of other diseases of similar domain.

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Table 3. Metrices of Xception

	COVID-19	NORMAL	PNEUMONIA
Precision	1.0000	0.8175	0.9400
Recall	0.9568	0.9655	0.8103
F1-Score	0.9779	0.8853	0.8703

0.8846

0.8682

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