COVID-19 Diagnosis using X-Ray Images and Deep learning

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***Abstract* – The year 2020 has witnessed the effects of global pandemic outbreak through the unprecedented spread of novel corona virus COVID-19. As the testing of coronavirus happened manually in the initial stage, the ever-increasing number of COVID-19 cannot be handled efficiently. Also, the coronavirus is divided into 3 phases and it has different effects on lungs. To handle this situation, researchers have attempted to detect coronavirus using chest X-ray images and Chest CT scan images by using Artificial Intelligence [AI] technologies. AI helps to forecast the coronavirus cases for analysing the virus structure and chest X-Ray and CT scan images helps to predict the stags of corona virus. Henceforth, this paper has developed a CNN model, which utilizes 3 classes as follows: positive COVID-19 images, normal images and viral pneumonia images. The model has been trained on these set of images and got 94% of accuracy on training dataset and 96% of accuracy on validation dataset. The proposed model has achieved the test accuracy of 94% for 3 classes in Chest X-Ray image classification. The main motive behind developing this model is to reduce its computational time by using less layers and more hyper parameter tuning. The proposed model is compared with pre-existing models as they were more complex and took much training time. Till now 94% of accuracy has been achieved on test dataset.**

Keywords-Convolutional neural networks, COVID-19, neural networks, X-Ray

I. INTRODUCTION

Coronavirus disease (COVID-19) is a newly founded coronavirus-caused infectious disease. It has affected many people around the world. It is basically divided into 3 phases. In very first phase people will feel like they have a fever, or their body will be in fatigue or a dry cough. In second phase they might have loss of taste or smell, a soar throat, diarrhoea, types of skin rashes. In third phase they will have breath shortness, a loss of appetite, a chest pain and they might a fever too. Most individuals infected with the COVID-19 virus will develop mild to moderate respiratory illness and recover without the need for any special care. Elderly people as well as those with underlying health problems such as chronic respiratory disease, diabetes, and heart disease are diseases that can cause a severe illness. It has affects in different ways to different people .Many people can have mild to moderate illness and they can recover without any treatment. There were many companies those tried to takeout many possible solutions to test coronavirus affected persons but as earlier most of the solution were manual so it took a lot of time to take out the results, around 2-3 days for the result. Then companies tried to use digital methods to detect the coronavirus. As the number of coronavirus patients are increasing day by day then we need a fast and an efficient method to diagnose a patient and where Artificial Intelligence is the best solution for diagnosis. The Artificial Intelligence is useful because we can give a set of images together and it will give us more accurate results. Only once we need to train our model on a dataset and then we can use it for coronavirus classification. Many people across the county have developed many models for coronavirus detection using machine learning and deep leaning algorithms and they have achieved a good accuracy too. But the main focus of my model is to develop a CNN model which is computationally efficient and will give good accuracy on smaller dataset too. As it was difficult earlier to find a dataset of Chest X-Ray images of COVID-19 patients. With the help of this model we would be able to detect the coronavirus even if we have a less number of dataset. CNN is complex and its only weakness is that it needs a lot of dataset for training but it is really good for classification.

II. LITERATURE REVIEW

Tulin et al. [3] has developed an automatic model for COVID-19 detection by using Chest X-ay images. Under this model they did two types of classification i.e. Binary classification (contained images of COVID and No-Findings) and Multi-class classification (continued images of COVID, Pneumonia and No-Findings).For study they used a DarkNet model as a classifier for "You Only Look Once" (YOLO) which is a real time object detection system. They used 17 layers of convolutional. They achieved 98.08% for binary classification and 87.02% for multi-class classification.

Khan et al. [4] in his paper he proposed a model named "CoroNet," which is a CNN model for COVID-19 diagnosis using radiography images of chest. The suggested method is based on the "Xception Architecture" which is a pre-trained model with the dataset of ImageNet and then it is trained on a dataset that was gathered from various publically accessible databases for research purpose. The average model result rate was 89.6 per cent and the recall and precision rate of COVID-19 cases is as follows: 93 per cent and 98.2 per cent for 4-classes (normal vs COVID vs. pneumonia bacterial vs. pneumonia viral). For the 3-class classification (COVID vs. Pneumonia vs. normal), classification performance achieved that is 95%.

Alazab et al. [16] in his paper tried to find COVID19 with the help of COVID19 X-Ray images. They used Chest X-Ray images because they are easily available and at a low price. For detection they used 3 Algorithms Short-term Memory Neural Network (LSTM), Autoregressive integrated moving average (ARIMA) model and the prophet algorithm (PA). They were successfully able to achieve 95- 99% F-Score. They PA gave the best performance overall. For COVID19 confirmation and recoveries they achieved 99.94 of percentage and 90.29 of percentage resp.

Shelke et al. [12] in her paper she did the classification on chest X-Rays images and designed a classification model which focused on accurate diagnosis of COVID-19. Their dataset contained the chest Xrays images that were divided into 4 classes are as follows tuberculosis (TB), pneumonia, COVID-19 and normal. They used VGG16 model which achieved the precision was 95.9 percent. [12]

Narian et al [13] has used 5 pre-trained convolutional neural networks which are based models (Inception-ResNetV2, ResNet50, InceptionV3, ResNet152 and ResNet101) used for detecting the COVID pneumonia infected patient which used chest X-ray Images. They used 3 different binary classifications algorithms by using 5-fold cross validation with 4 classes as follows (COVID-19, bacterial pneumonia, normal and, viral pneumonia).The ResNet50 model gave the best classification performance which is 96.1% of an accuracy on Dataset-1 and 99.5% of an accuracy on Dataset-2 and 99.7% of an accuracy on Dataset-3 in comparison to other 4 models.

Asif et al [14] in her paper tried to the detection of COVID□19 pneumonia automatically in patients using chest x□ ray imaging while improving the accuracy in detection using deep convolutional neural networks (DCNN). The dataset contained images Normal Chest X-ray, Viral pneumonia and COVID-19 pictures as follows 864 of COVID□19, 1345 of viral pneumonia and 1341 of normal chest x□ray images. In this they have used deep convolutional neural networks based model that is Inception V3 with transfer learning for detection of which achieved a classification accuracy more than 98% (where the training accuracy was 97% and validation accuracy was 93%).

Hussian et al [15] has developed a CNN model that is called CoroDet has created for automatic COVID19 detection. In which they used raw images of Chest-Ray and CT scam images. CoroDet was used for 3 types of classifications, diagnosis of 2 class classification of COVID and Normal person, 3 class classification of COVID, Normal, and non-COVID pneumonia persons, and 4 class classification of COVID, Normal, non-COVID viral pneumonia and non-COVID bacterial pneumonia persons. For 2 classes classification they achieved an accuracy of 99.1%, for 3 class got 94.2% of classification accuracy and 91.2% for 4 class classification.

Azemin et al [18] had used a deep learning model, which is based on the ResNet-101 CNN network architecture that has learned to recognize objects from a million images and then re-trained to detect anomalies in chest X-ray images. The efficiency of the model was 0.82, 77.3 per cent, 71.8 per cent and 71.9 per cent respectively in terms of area under the receiver operating curve, sensitivity, precision and accuracy.

Yang et al [19] in this paper they took a dataset of around 216 people of CT scan images of positive COVID-19 people and around 463 people were non COVID-19 patients. In this paper they have developed an CNN model which have these following things Random horizontal flip, random cropping with a size of 0.2 in area, random colour jittering such as random brightness with a ratio of0.4, random contrast with a ratio of 0.4, random saturation with a ratio of 0.4, random hue with a ratio of 0.1, Gaussian blur, and random gray-scale conversion are all applied to each input image. The dynamic dictionary was set to 512 entries. The optimizer they used was stochastic gradient descent and mini batch was of 128. They weight decay was 0.0001, the momentum was 0.9 and the learning rate was 0.015. Using this dataset and they have achieved an accuracy of 0.89% and the Area under Curve was 0.98%.

Zheng et al. [20] In this paper, they have trained a deep learning algorithm which is a fast way to detect the COVID.-19 patients. The algorithm took 1.93 seconds to process the CT image of a single patient. It can correctly estimate the risk of infection with COVID-19 in chest CT volumes without the need for training lesions to be annotated.

Tuncer et al. [21] have developed a model called an Exemplar model. First of all they applied Fuzzy Tree Transformation on each image then exemplar division was implemented on them. Then they used Multi-Kernel local binary pattern for feature generation where most of the features were selected using Iterative neighbourhood component feature selector. Afterwards these images were processed using few algorithms like decision tree, support vector machine (SVM), K-nearest neighbour (k-NN). They achieved the best accuracy of about 97.01%using SVM.

Elkorany et al. [22] have proposed a model for detection and classification of COVID-19. For feature extraction they have utilized ShuffleNet and SqueezeNet architecture, which supports to extract deep features. For two class classification (i.e. COVID/Non-COVID) was 100% and for three class classification (i.e. COVID, Normal and Pneumonia) it was 99.72 % of accuracy. In paper they also presented the recall, Specificity, Precision, F1-Score and Accuracy which was above 80% if method is used SqueezeNet and similar for ShuffleNet, the values were above 80%

III. PROBLEM STATEMENT

Availability of dataset is the main issue, whenever a new disease spreads across the globe. The predictions cannot be made on small dataset, which might not give accurate results. Proposed model can also be used to make predictions using less dataset and also with robust accuracy.

Developing and implementing a model will give robust predictions on a smaller dataset.

IV. CHALLENGES

In CNN, Large volume data is required with more hyper-parameter tuning to extract the optimal features.

Robust accuracy on smaller dataset.

V. METHODOLOGY

A. Dataset

This research work has used the dataset from Kaggle, which contained chest X-ray images of a normal person and infected person. The database contained the chest X-Ray images of COVID-19 positive cases, Normal chest X-Ray images and Viral Pneumonia chest X-Ray images [6]. Images are as follows: -

- **219** images of COVID-19 Positive images
- **1341** images of Normal images
- **1345** images of Viral pneumonia images

Images are in PNG format. The dimension of images is 1024*1024 pixels.

Both chest x-rays were originally tested for quality assurance for the review of chest x-ray images, by deleting all low-grade or unreadable scans. Two specialist doctors were then tested for image diagnosis before being accepted for AI testing. A third expert also reviewed the assessment collection in order to account for any scoring errors. The connection to the dataset is available here.

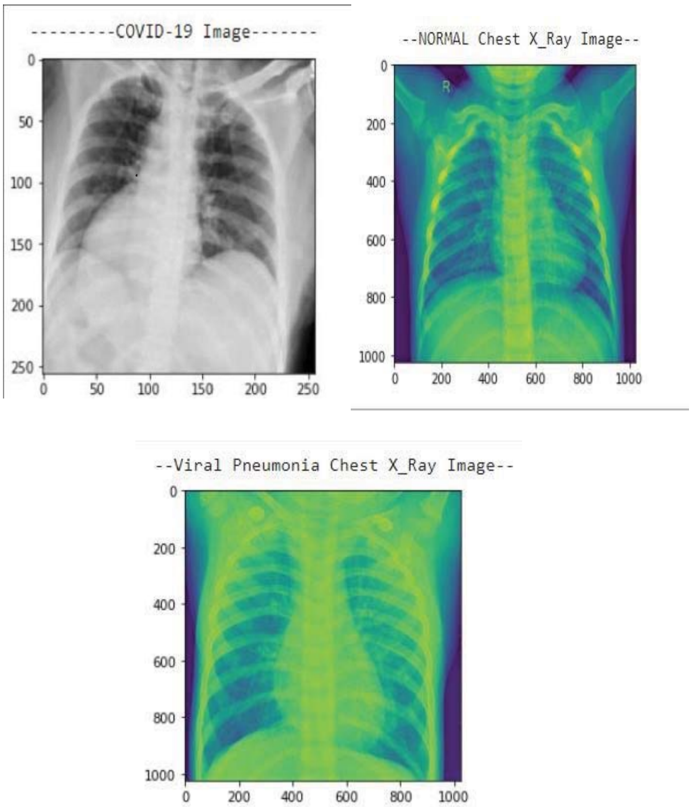

FIG 1: Sample Images of COVID19, Normal and Viral Pneumonia

B. Pre-Processing

In pre-processing, the proposed dataset is increased by augmentation technique called "Image Data Generator". Image data generator generates more data by applying small changes on it like brightness, zoom, horizontal flip, shifting etc. Using Image Data Generator which also include pre-processing (like edge sharpness, brightness etc.) on COVID Image dataset as its dataset was less as compare to other categories in the dataset.

Table 1: Number of images after augmentation

Augmentation	**Covid-19 images after augmentation**	**Normal Chest X-ray images**	**Viral Pneumonia images**
205	1363	1351	1345

C. Convolutional Neural Network (CNN) Model

A neural network is called a convolutional neural network, designed to handle multidimensional data such as image and time series data. During the training process, this includes the extraction of features and weight calculation during the training. The identity of such networks is obtained by the use of a convolution operator, which is useful for solving complex tasks [23-24].

D. Feature Extraction

CNNs have an automatic feature extraction feature, and that is the key feature. The established source information is usually forwarded to the Extraction Network function, and the resultant extracted features will be forwarded to the Classifier Network. Various convolutional and pooling layer pairs are used in the process of feature extraction. A series of convolution filters are passed to perform an input data convolution process. As a dimensional reduction layer which defines the threshold, the pooling layer is used. A number of parameters must be changed during back propagation, which in effect minimizes interactions within the framework of the neural network.

- **Strength** – It is most commonly used in deep learning applications with different training methods that offer reasonable results for multi-dimensional data; abstract significant features can be derived from original data.
- **Weakness**- Large volume of dataset is required to have more hyper-parameter tuning to extract the optimal features.

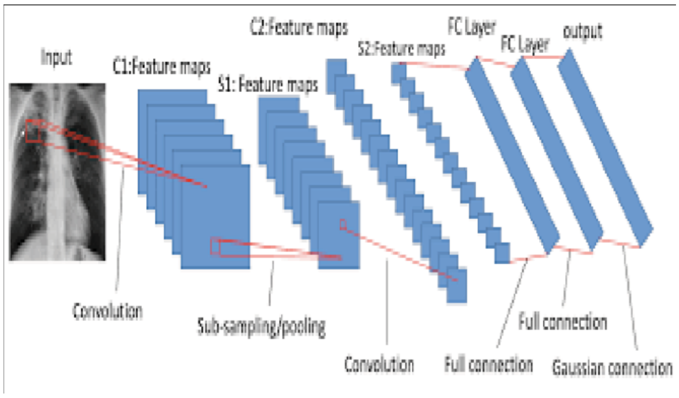

FIG 2: Architecture of CNN Model

E. Summary of Model

The proposed CNN Model has used 5 convolutional layers, 5 pooling layers and 3 dense layers. The sequence is like the first used Convolutional layer then a Maxpooling layer then again its repetition till 5 Convolutional and 5 Maxpooling layer and after it I have used two fully connected dense layers and one output layer. In the first Convolutional layer there were 32 filters with filter size as 3x3, Stride as 1x1, padding as same and Activation function used is ReLu. Then I have increased the number of filters in each layer as 32, 64, 128, 256, and 512 with same hyper parameters. In Maxpooling layer the pool size was 2x2, strides as 2x2 and padding as valid till 05 Maxpooling layers. In first fully connected dense layer I have used 256 neurons with L2 regulizer at the rate of 0.001 and in second fully connected layer there is 512 neurons with L2 regulaizer at the rate of 0.001. In the last dense layer the neuron is the number of the classes with Softmax activation function. The Loss function that I have used is Categorical Crossentropy and Optimizer is Adam at the learning rate of 0.0001.

Table 2: Summary of CNN Model

Layer	Output Shape	Kernel Size/Pool Size	Neurons in Layers	Activation function/Dropout Value	Parameters
Convolution_1	256*256*3	3*3	32	Relu	896
Maxpooling1	128*128*32	2*2			0
Covolution_2	128*128*64	3*3	64	Relu	18496
Maxpooling2	64*64*64	2*2			0
Convolutio_3	64*64*128	3*3	128	Relu	73856
Maxpooling3	32*32*128	2*2			0
Convolution_4	32*32*256	3*3	256	Relu	295168
Maxpooling4	16*16*256	2*2			0
Convolution_5	16*16*512	3*3	512	Relu	3277312
Maxpooling5	8*8*512	2*2			0
Flatten	32768				0
Dropout	32768				0
Dense_1	256		256		8388864
Dense_2	512		512		131584
Dropout	512			0.5	0
Dense_3	3			Softmax	1539
Total parameters					418339

VI. RESULT AND ANALYSIS

The database contained 3 types of images that are Normal, Viral Pneumonia and COVID19 Positive. I have tried 3 Algorithms as follows CNN, VGG16, and VGG19 for multi-classification of these 3 classes, where all performed well in the classification. The main motive of my algorithm is COVID19 classification. Where we can see the precision for COVID19 is 1.00 and for VGG16 and VGG19 is 0.95 and F1 score and Recall for my CNN model for COVID19 is 1.00 whereas F1 score and Recall for VGG19 and VGG16 is same i.e 0.97 and 1.00 for COVID19.

We can see all three algorithms are giving good results but if we do comparison of Accuracy the VGG16 and VGG19 are giving better accuracy (i.e 97%) than my CNN model(i.e 94%). But VGG16 and VGG19 uses more computational power where my CNN model took less computational power in comparison to VGG16 and VGG19.

Table 3(a): Classification report of CNN model

	Precision	Recall	F1-Score
Normal	1.00	0.70	0.83
Viral Pneumonia	0.78	1.00	0.88
COVID19	1.00	1.00	1.00
Accuracy	0.94		
AUC	0.985		

Table 3(b): Classification report of VGG16 model

	Precision	Recall	F1-Score
Normal	1.00	0.86	0.92
Viral Pneumonia	1.00	1.00	1.00
COVID19	0.95	1.00	0.97
Accuracy	0.97		
AUC	1.00		

Table 3(c): Classification report of VGG19 model

	Precision	Recall	F1-Score
Normal	1.00	0.86	0.92
Viral Pneumonia	1.00	1.00	1.00
COVID19	0.95	1.00	0.97
Accuracy	0.97		
AUC	0.97		

F. ROC Curve

In the ROC curve we can see that the curve is closer to the top-left corner which indicates the best performance [25]. With the ROC curve, we aim to find a good model that will maximize the compromise between the FPR and True Positive Rate (TPR). The area under the curve is what is critical here (Curve area=AuC). The ideal 100% curve, so that you can discern 100% of the time between negative and positive effects (which is almost impossible in real life).

CONCLUSION

The CNN model used for classification has achieved accuracy of about 94% on test data for 3 classes classification, which contains only 32 images from all categories and its recall and precision rate for COVID19 are as follows 94 % and 95% , wherein VGG16 model has achieved 97% of accuracy and VGG19 has achieved 97% of accuracy for 3 classes classification. The proposed CNN model provides good accuracy on less number of layers and less number of epochs in comparison to pre-trained models.
This CNN model is better than other models as it is less complex than others and achieving good accuracy on training, validation as

well as on test dataset. As we can see VGG16 and VGG19 are the models which have 16 and 19 layers where in comparison my model has only 7 layers. If we'll talk about the training time VGG16 and VGG19 are taking too much time to train the model. For now I'm comparing my model on this accuracy i.e. 94%, as I'll modifications on my model to increase the accuracy further for better comparison.

Table 4: Performance Comparison of Models

Model	**Number of layers**	**No. of epochs**	**Accuracy on test dataset**
CNN	7	31	94
VGG16	16	100	97
VGG19	19	50	97

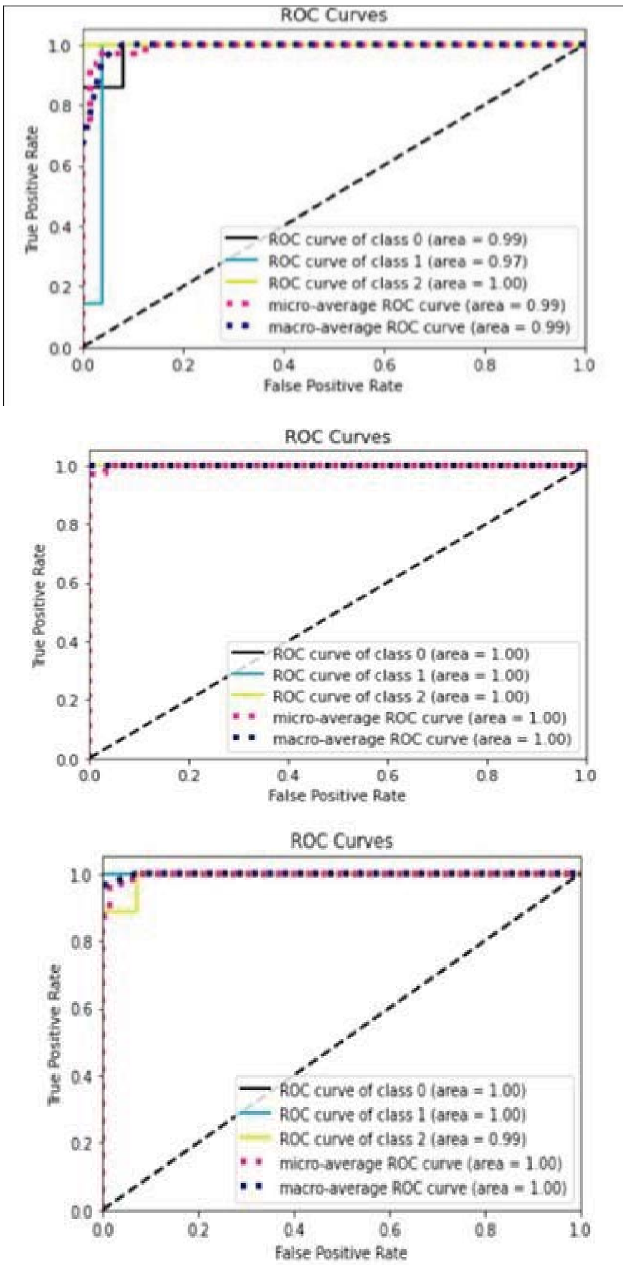

FIG 3: ROC Curve of CNN, VGG16 and VGG19 Resp.

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