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Leveraging Deep Learning and Radiography for Diagnosis Of COVID-19

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***Abstract*—**Today, Machine learning and Deep learning are being leveraged by almost every industry all over the world. They have now become ubiquitous tools for research in the fields of Robotics, Autonomous cars, Computer vision, medical and health sciences to name a few. In this article the equip frontiers of Deep learning and Computer Vision are used to diagnose COVID-19. The primary clinical method that is currently in use for the diagnosis of COVID-19, Reverse Transcription Polymerase Chain Reaction (RTPCR) is expensive and requires trained medical personnel. Radiography is an easily accessible tool that can be a reasonable alternative to RT-PCR in diagnosing COVID-19. A Convolutional Neural Network based on VGG16 architecture is trained and analyzed on around 21000 lung X-ray images using transfer learning. Out of the 21170 images obtained from kaggle repository, 16500 images have been used for training, 3130 have been used for validation and 1540 for testing the validated model. The goal is to accurately screen the patients suffering from Covid-19 against those who also suffer from Ground Glass Opacity and Viral Pneumonia which have a similar effect on human lungs as that of Covid-19. In the result analysis, the model gives a train accuracy of 99% and a validation accuracy of 94.16%. The proposed model helps radiologists diagnose COVID-19 within 0.5 seconds in a system equipped with GPU (Graphic Processing Unit) by classifying thousands or even millions of images in a single click. When trained with a larger dataset, the model may lead to facilitating early treatment of such lethal disease resulting in improved clinical outcomes. This work proposes a possible method of screening COVID-19 infected patientsbut do not claim any medical accuracy.

Keywords*-*COVID-19, VGG16, TPU, Ground Glass Opacity, Viral Pneumonia, Scatter plot, Sofmax, ReLU, Keras, Categorical Cross Entropy, Adam Optimizer, Precision, Accuracy, Recall, F1 score, Confusion matrix.

I. INTRODUCTION

COVID-19 (Corona Virus Disease 2019) disease declared as a pandemic by WHO has caused millions of deaths and has adversely affected the livelihood of people across the globe. Scientists in the last decade have

worked on viruses like SARS (Severe Acute Respiratory Syndrome), [1] MERS (Middle East Respiratory Syndrome) [2, 3] etc and the world has been able to contain these viruses since the vaccines were prepared and administered to people in a lucid manner without a considerable delay. But in the present scenario, the vaccination phase for COVID-19 does not seem to be completed in near future especially in a country like India but an exact proven alternative solution is not found till date[4]. Even today, people are dying of COVID-19 and the diagnosis cost is also high in the context of country and individuals [5]. Diagnosing COVID-19 against other diseases which have a similar effect on lungs is quite challenging and rigorous procedures are required to reduce the risk for patients.

One of the critical observations pertaining to this epidemic is that it affects the throat of the patient in the initial phases followed by difficulty in breathing. On the other hand, it has been reported in many cases that this disease has no effect in the initial phases. So naive diagnosis is clearly not the solution for screening the infected ones. Besides, allegedly infected patients need to be in isolation and require adequate medication so that healthy people might not be infected. New strains of the virus have been detected in several countries and have already spread to many countries. Subsequently, there has been a rapid rise in cases in recent days proving that the infection is a chain process. Thelung X-ray images of COVID-19 affected patients and healthy peopleare made available for analysis on online repositories like Kaggle and GitHub from March 2020 [6]. Hence medical imaging [7] is a promising method of analyzing and diagnosing COVID-19 and can also aid in screening COVID-19 infected patients against those infected by other diseases like Lung Opacity and Viral Pneumonia which have a similar effect on lungs as that of COVID-19 with the help of chest X-Ray images. Having understood the significance of radiography-based diagnosis, we collected the Lung X-ray images of patients infected with COVID-19, Ground Glass Opacity or Lung Opacity and Viral Pneumonia along with those of healthy patients from Kaggle repository and applied Deep Learning to classify these appropriately. We have analyzed the collected data using a Convolutional Neural Network (CNN) based on VGG16 (Visual Geometry Group) [8] based architecture for the initial layers of the network adopting the approach of transfer learning. This work mainly focuses on leveraging CNNs to diagnose and classify COVID-19 from other similar in-effect diseases.

Section 2 of the article presents the related works which proposed different frameworks and methods for analyzing and diagnosing COVID-19. Advantages and anomalies in each of these methods are also discussed. Section 3 discusses the attributes of the dataset and provides the visualizations to interpret the data acquired from Kaggle repository. This section also discusses the development environmentused to train and validate the model. In Section 4, we discuss the model formulation and the proposed algorithm to classify the data and diagnose COVID-19. Subsequently, Section 5 discusses the metrics used for evaluating the trained model and presents the resulting plots of these metrics through the training and evaluation phases. Finally, we conclude

this paper on our work in Section 6 and briefly discuss our future endeavors in leveraging deep learning for diagnosing several other diseases and PCB (Printed Circuit Boards) defect detection.

II. RELATED WORK

Researchers across the world have proposed several frameworks and models to diagnose COVID-19 over the last 12 months. In [9], a framework named COVID-CAAPS based on capsule networks to detect COVID-19 disease using X-ray images is proposed. They have overcome class imbalance using convolution layers and capsules has overcome in the analysis. Their model shows an accuracy of 95.7% with a smaller number of trainable parameter set. In [10], the authors have built CNNs based on ResNet, Xception V3 and Inception architectures to diagnose COVID-19 with the help of 6432 X-ray images of chest. They have concluded that Xception model gives the highest accuracy of 97.97% in deciding if the person is infected with COVID-19. Nevertheless, there are several other prominent CNN architectures which the authors have ignored in the paper. Furthermore, the paper does not distinguish COVID-19 from other diseases which have a similar effect on lungs of a patient. In addition, in [11], the protocols the hospital staff should follow to minimize the risk of healthy patients being diagnosed with COVID-19 has been discussed.

In [12], the authors have used Local Binary Pattern (LBP) to find out the characteristics of chest X-ray images. Subsequently,they have applied SVM (Support Vector Machine) technique to diagnose Pneumothorax. They have used multi-scale texture segmentation to remove the impurities present in the chest X-ray images and segmented the abnormal regions of lungs. Next up in [13], the authors introduced a model named COVID-RENet to extract edge and region-based features that uses CNNs for classification and SVMs to tweak the classification performance. This model is especially meant for medical specialists which can aid in early diagnosis of COVID-19. Interestingly in [14], the authors have discussed different methods of diagnosing COVID-19 and the challenges faced in the process. They called for an automated method of diagnosing COVID-19 to contain the virus spread. After analyzing some chest X-ray images to detect Pneumonia, it is concluded that it is difficult to predict that COVID-19 causes Pneumonia in addition to other symptoms. In [15], the authors have discussed the role of Artificial Intelligence (AI) and Machine Learning (ML) in healthcare and medicine. They have also discussed the challenges in implementing ML models with lesser number of images as input data. Furthermore, they have collected chest X-ray and CT (Computer Tomography) scans from several sources and applied transfer learning using pre-trained AlexNet and a modified CNN with accuracies of 98% and 94.1% respectively. In [16], the authors have introduced a novel architecture called as KE Sieve Neural Network Architecture which also uses chest X-ray images to analyze COVID-19. The proposed model shows an accuracy of 98%. In [17], the authors have discussed the use of Deep Anomaly Detection to screen COVID-19 infected patients. However, the dataset obtained was small with only 100 X-ray images in which 70 were of COVID-19. Finally, in [18], the authors have discussed how to use thermo plasmonic in diagnosing COVID-19.

III. DATASET VISUALIZATION AND DEVELOPMENT ENVIRONMENT

The dataset for training, development and testing the model has been obtained from Kaggle repository which comprises lung X-ray images, all the images are in Portable Network Graphics file format with a resolution of 299*299 pixels of patients infected with COVID-19, Ground Glass Opacity or Lung Opacity, Viral Pneumonia along with those of healthy people. In the second update, it consists of 21170 lung X-ray images out of which 3616 images are of COVID-19, 6012 images are of Ground Glass Opacity, 1345 images are of Viral Pneumonia and 10200 lung X-ray images of healthy people. This dataset is further divided into training, validation and testing sets each consisting of 16500, 3130 and 1540 images respectively so that the training set comprises 80% of the data obtained. It should be noted that no data cleansing is required in this case. As per the bar graph presented in Fig. 1, healthy and Ground Glass Opacity samples compose 80% of the dataset. So, an interesting challenge for the model is plausible difficulty in identifying COVID-19 and Pneumonia samples. Fig. 2 shows three random samples from the dataset for each class. From the figure, it can be concluded that the dataset consists of grayscale images.To examine the patterns between image color values and their class, it is imperative to plot the distribution of mean, max and min pixel values for each class in the dataset. The top-left plot in Fig. 3 shows the distribution of mean color value for the entire dataset. The other plots in the figure present the mean, maximum and minimum color value or pixel value distribution by class. An interesting observation is that Viral Pneumonia is the only class with near Normal distribution in all the three plots. Also, it is the class with lower max values when compared to other classes. Clearly, the density of images in all the classes peaks at around 255 which is the maximum possible value. Further, the distribution of mean values is similar in case of Normal and Ground Glass Opacity images. Whereas, COVID-19 and Viral Pneumonia present a similar distribution of Max values in their images.

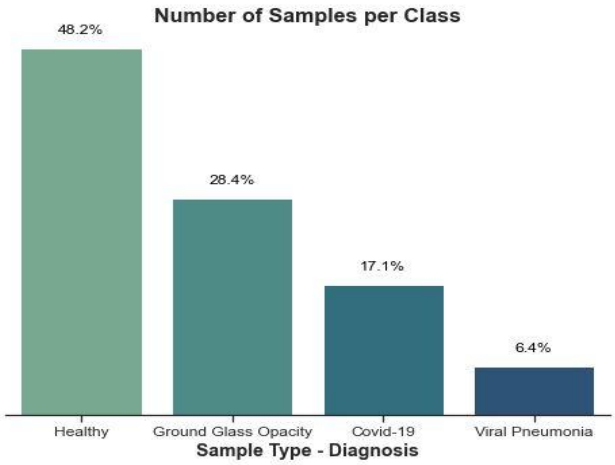


Figure 1. Percentage of samples in each class

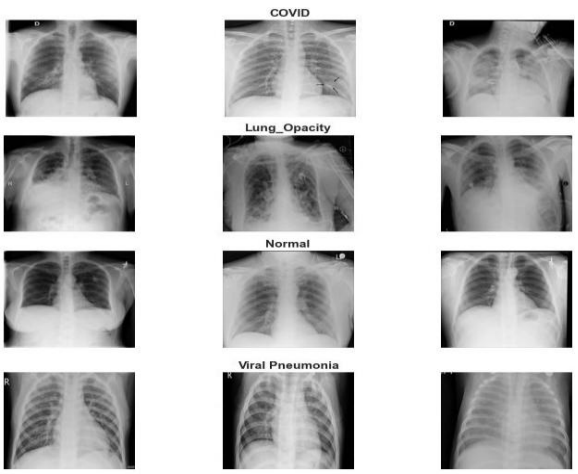


Figure 2. Random images from each class.

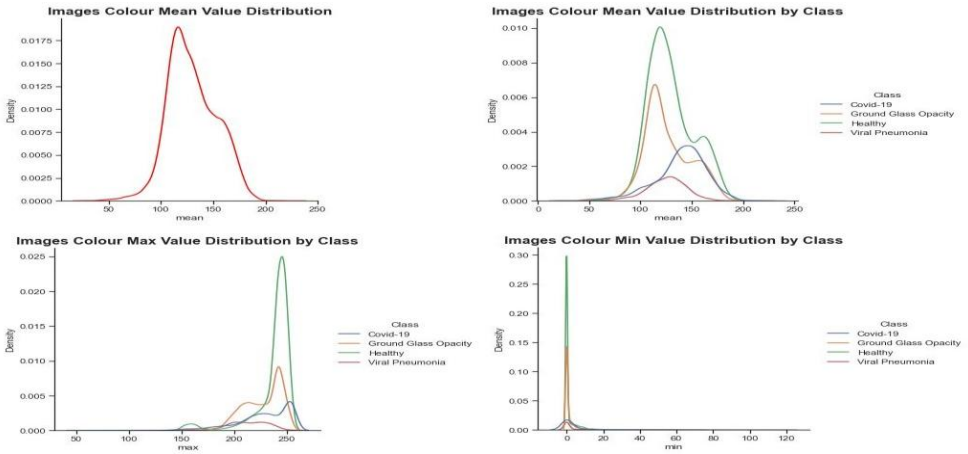


Figure 3. Images mean, max and min value distribution by class.

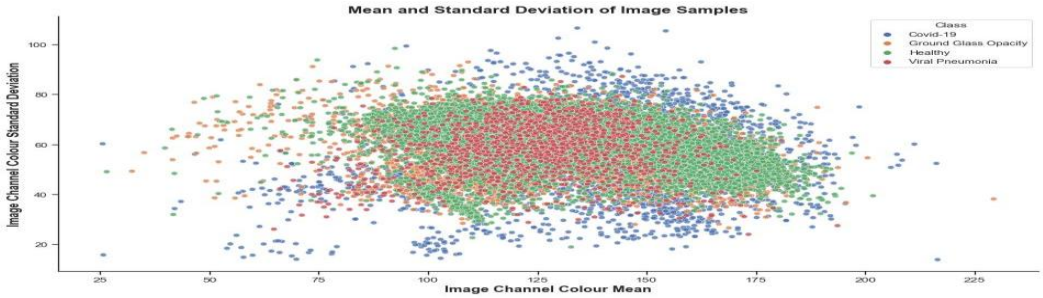


Figure 4. Scatter plot showing the mean and standard deviation of pixel values.

Fig. 4 analyses the relationship between the mean value and standard deviation of images in the dataset.Each class is distinguished by a different color. Most of the images occupy the central region of the scatter plot and hence there is not much contrast in their pixel values. This sets a right context for leveraging Deep Learning to classify the images accurately. From the figure, COVID-19 is the only class whose samples form a small cluster towards the bottom-left of the plot where the values of mean and standard deviation are low. Since the dots of all the classes are on top of each other, an individual scatter plot is necessary for each class to obtain some important details. Fig. 5 presents the scatter plots of mean and standard deviation for each of the classes individually. The figure shows that the normal and Ground Glass Opacity samples have a similar scatter with outliers having higher standard deviation and lower mean values. However, samples of Viral Pneumonia present a concentrated plot which shows that these images have higher correlation with each other. COVID-19 scatter is peculiar in the sense that unlike any other class, the points are scattered across the entire plot even though they are less in number compared to Normal and Lung Opacity images. This shows that there is a clear distinction among the samples of COVID-19. The visualization in Fig. 6 presents the obtained samples from repository in a chart format. In the chart, the crescent brightness of the images increases as their mean value increases. Higher values of standard deviation constitute images that have higher contrast and a dominant black background.

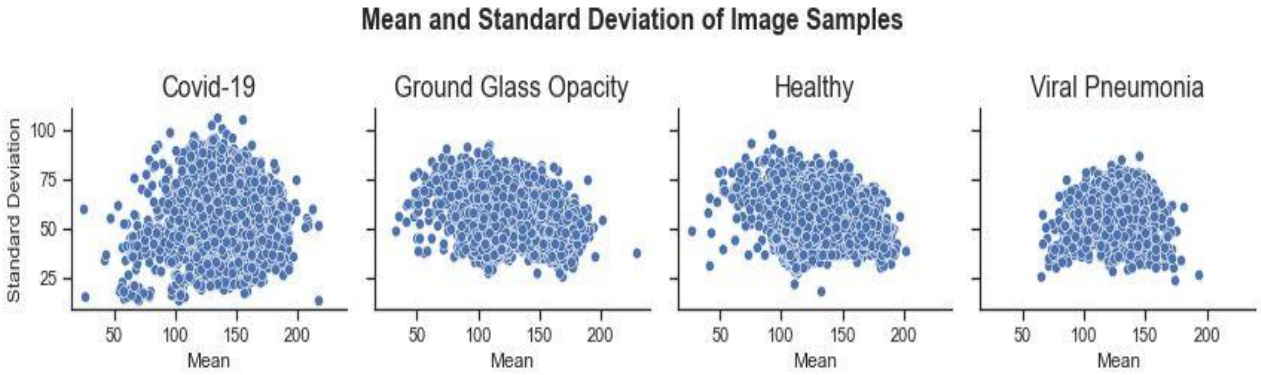


Figure 5. Mean and standard deviation of pixel values for each class

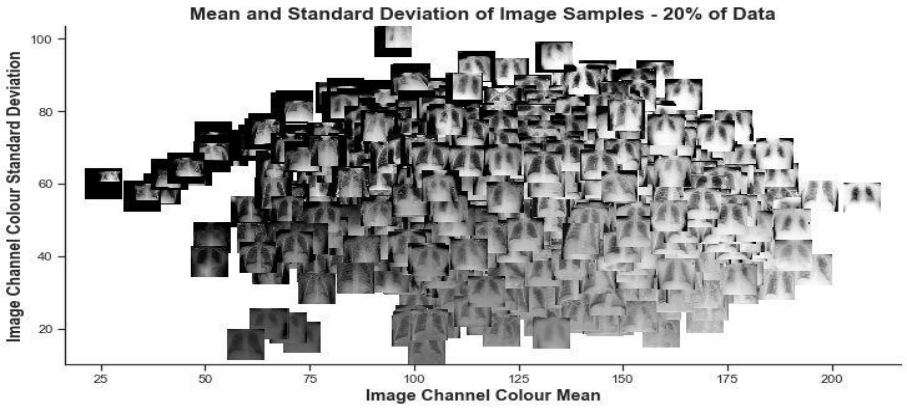


Figure 6. Obtained lung X-ray images in a chart format replacing the dots in the scatter plot

The model has been trained and validated on Google COLAB platform which is a very useful tool for executing deep learning algorithms as it gives free access to dedicated GPUs and TPUs (Tensor Processing Unit). The base hardware for the training face of the model is the TPU offered by Google over the cloud. A TPU is a hardware accelerator specialized for deep learning tasks. It shortens the training time by performing matrix multiplication in the hardware. TPU is a 65,536 8-bit MAC matrix multiply unit that offers a peak throughput of 92 TeraOps/second (TOPS). According to the authors, the matrix unit uses systolic execution to save energy and time by reducing reads and writes of the buffer. Subsequently, the validation and testing phases were carried out on Tesla K80 GPU over the cloud.

IV. MODEL FORMULATION

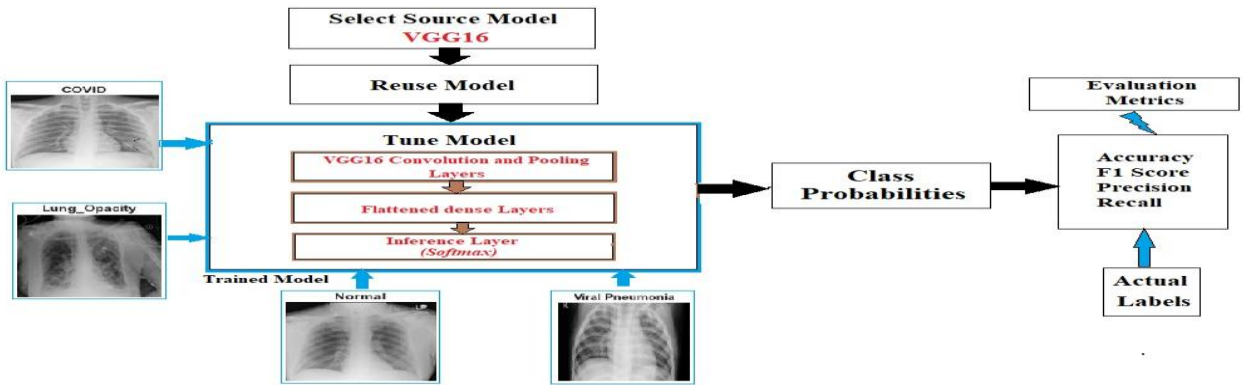


Figure 7. Proposed Model for classification of X-ray images.

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 9, 9, 512)	14714688
flatten_1 (Flatten)	(None, 41472)	0
dense_4 (Dense)	(None, 256)	10617088
dense_5 (Dense)	(None, 256)	65792
dense_6 (Dense)	(None, 4)	1028

Total params: 25,398,596
Trainable params: 10,683,908
Non-trainable params: 14,714,688

Figure 8. Model Summary

As stated in the previous section, no data cleansing is required for the obtained dataset. The model has been built using the approach of Transfer Learning. This is a popular method where a model or network built for some task is reused for initial layers of a new model built for a specific purpose. To be more specific, the model uses the Pre-trained model approach which includes the steps of selecting a source model, reusing the source model and tuning the model. The biggest benefit of this approach is that a concrete model need not be trained from scratch for a given target task given the large number of weights in each CNN layer which in turn span across multiple layers. This reduces the training time significantly and hence offers a good amount of time to validate and analyze the results.Fig. 7 summarizes the flow of Transfer Learning approach applied for the model and Fig. 8 summarizes the fully connected layers and total trainable parameters.

A. A Note on CNNs and VGG16

One of the challenges of Computer Vision problems is that the number of inputs to layers of a Neural Network can get really big. For example, the number of input parameters from a 1MP image is 3 million and if the first hidden layer of the neural network has 1000 neurons, the weight matrix of this layer has the dimensions, 1000x3M summing up to 3 billion weights. So, the computation cost and memory requirements are huge if a normal neural network is trained with images. Convolutional Neural Networks solve this problem by employing 'Convolution' as their key operation. Fig. 9 shows the edge detection performed by a convolution layer in a CNN. The input is one of the three color channel matrices (dimensions are 6x6) of an image whose vertical edges are to be detected. It is then convolved with another matrix called as a filter which is of dimensions 3x3. The filter is applied to each of the 3x3 sub-matrices of the input matrix. The result of this 3x3 convolution is the first element of the output matrix indicated by the same color as that of the corresponding sub-matrix. Thereafter, an activation function such as ReLU (Rectified Linear Unit) is applied to the output matrix before passing this matrix as input to the next layer. In practice, the input image consists of three channels and hence the filters are also three dimensional instead of being two-dimensional. There exists another layer apart from the convolutional layer called as Max pooling layer. In such layer, the

filter when convolved with sub-matrices of the same dimensions, outputs the maximum value in each of the sub-matrices.

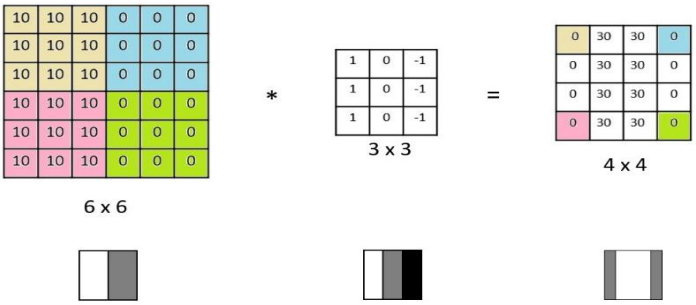


Figure 9. Vertical Edge Detection using a 3x3 Convolutional filter.

A remarkable thing about VGG16 is that it has much simpler structure and lesser hyperparameters when compared with other CNN architectures. It uses a 3x3 convolutional filter with a stride of 1 and 2x2 Max Pooling filter with a stride of 2 in all the layers. The padding is also same for all the layers. The relative uniformity of the architecture made VGG16 a quite attractive choice to researchers. Fig. 10 shows the architecture of VGG16 with all the convolutional and pooling layers. The network has 13 convolutional layers and five max pooling layers. It comes with three fully connected layers towards the end followed by a Softmax layer that was originally intended to classify 1000 different classes from the ImageNet database. The number 16 in the title signifies 13 convolutional + 3 fully connected layers. The proposed model takes the pre-trained VGG16 CNN, replaces the original fully connected layers of 4096 nodes with fully connected layers of 256 nodes as shown in Fig. 8. The initial 13 Conv layers and pooling layers together act as feature extractors for the obtained dataset of X-ray images.

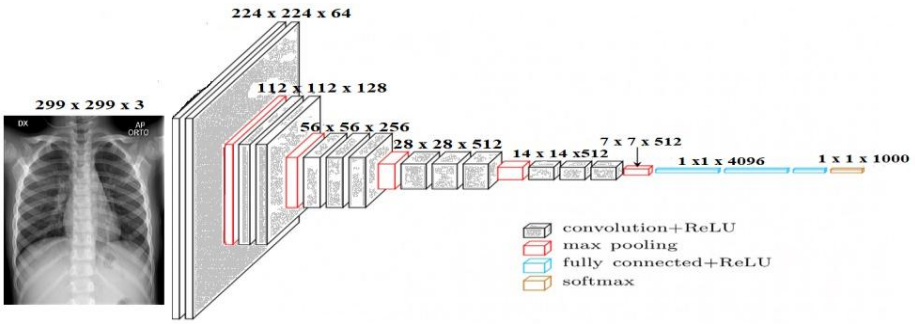


Figure 10. VGG16 Architecture

B. Loss Function: Categorical Cross Entropy

A loss function is used to optimize the parameters of the model so as to fit the model for the data. Since the model is based on multi-class classification, Cross Entropy is the best choice of loss function. Cross-entropy is the difference between two probability distributions for a given set of events. Categorical cross entropy is a specific case of Cross entropy used for problems involving multi-class classification. Here, the

target or the ideal output is one-hot encoded vector where the value of the output corresponding the correct class is 1 and all others are zeros. The value of the loss function decreases with each epoch through the dataset. The model is trained with Adam Optimizer at a learning rate of 0.001 and loss function as Categorical Cross entropy.

$$L(X,\hat{X}) = -(\sum X * \log(\hat{X}) + (1-X) * \log(1-\hat{X})) \quad (1)$$

Where X = True Label, $\hat{X}$ = Predicted Label, $L(X,\hat{X})$ is the Loss Function.

C. Proposed Algorithm

Below is the methodology used to train the model explained in steps.

1) Preprocessing the X-Ray Images: The images are stored in a directory where each sub-directory contains images of a specific class. So the model uses ImageDataGenerator() function of Keras API (Application Program Interface) which accepts the images as per their corresponding sub-directories and generates input and output labels automatically. In addition it also performs data augmentation as follows:

a) Reshaping the images: It reshapes an image to dimensions (299, 299, 3) as per the dataset for better performance.

b) Random Rotation Range: 5°

c) Zoom Range: 0.2 (In proportion with the image size).

d) Width Shift Range: 0.2(In proportion with the image size).

e) Height Shift Range: 0.2 (In proportion with the image size).

2) Applying the X-Ray images as input parameters to the input layer of pre-trained model (VGG16 functional).

3) Capture the outputs of the ultimate convolutional layer of pre-trained model.

4) Flatten the dimensions of these outputs to n x 1.

5) Add the Dense layers or Fully Connected Layers with number of hidden units = 256. Without activation, the outputs of dense layers are of the form:

$$Z = W * A + b \quad (2)$$

6) Apply activation function to the dense layers.

A = ReLU(Z)

$$ReLU(Z) = \max(0, Z) \quad (3)$$

7) Add a dense layer with Softmax as the activation function.

$$softmax(Z_i) = \frac{e^{Z_i}}{\sum_{j=1}^{k} Z_j} \quad (4)$$

Where Z_i = Output of the i^{th} node of dense layer

V. EVALUATION METRICS AND RESULTS

When performing classification, the usual outcomes are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) for each of the classes. TP is when the model predicts that an X-ray image belongs to a specific class and it actually belongs to that class. Whereas TN is when the model predicts that an X-Ray image does not belong to a class and it actually does not belong to that class. In the above two cases, the model is truly successful and accurate. On the other hand, FP and FN result when the model is not accurate. FPis when the model predicts that a given X-ray image belongs to a class but it actually does not belong to that class. Finally, FN is when the model predicts that a given X-ray image does not belong to a class but it actually belongs to that class. Hence for a better understanding and evaluation of a trained model, a confusion matrix is plotted with four of these outcomes for each class on testing data in Fig. 11. It basically shows the number of TPs, TNs, FPs and FNs resulted when test data are passed as inputs to the validated model.The total number of True Negatives for a class is the sum of the elements in all the rows and columns excluding the row and column of that class. Based on these four outcomes, several evaluation metrics are defined as follows.

A. *Precision:*

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (5)$$

B. *Recall:* It defines the True Positive rate of the considered class. It is commonly called as Sensitivity [24].

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (6)$$

C. *F1 Score:* This metric performs well on an imbalanced dataset as it takes into account both the False Positives and False negatives.

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (7)$$

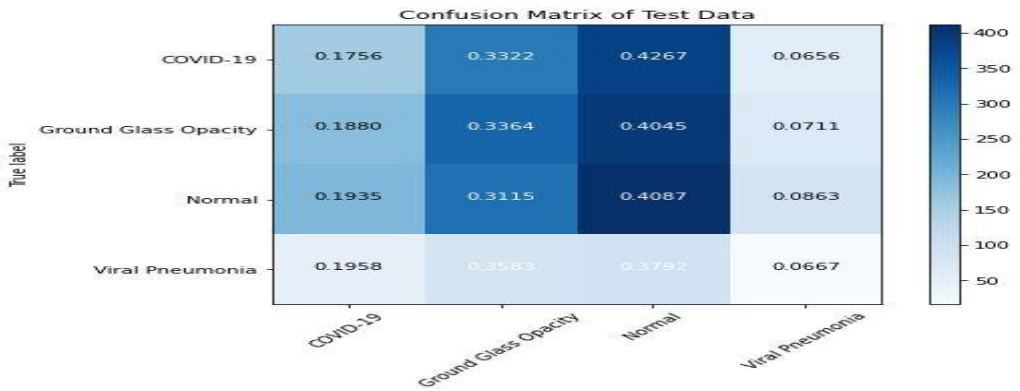


Figure 11. Confusion Matrix for Test data.

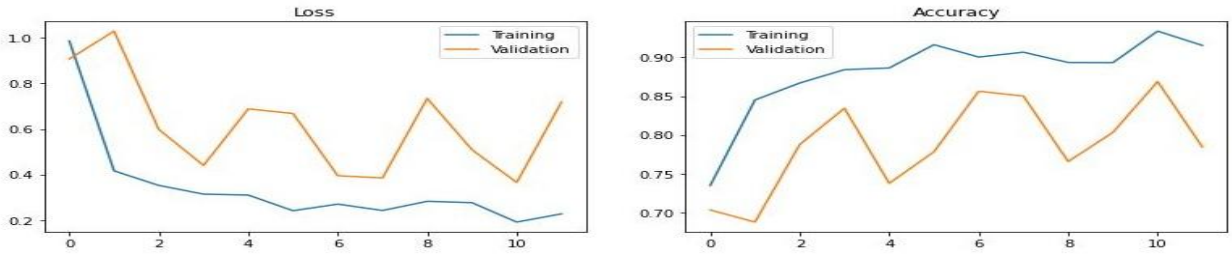
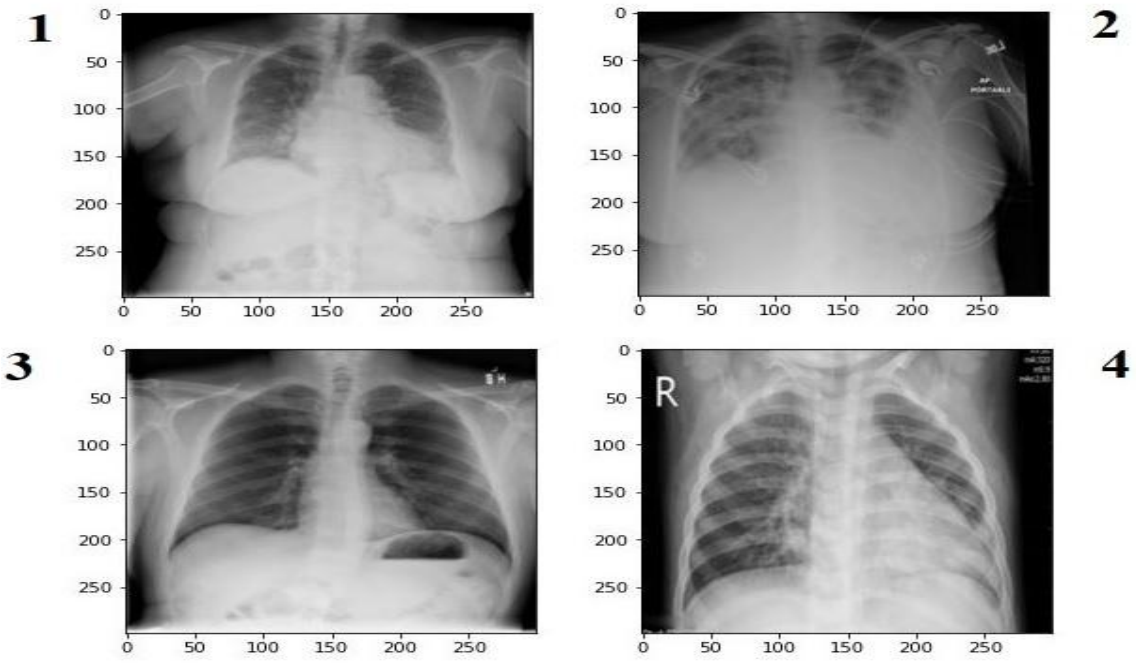


Figure 12. Categorical Cross Entropy loss for Training and Validation sets-Left. Accuracy of model for Training and Validation sets-Right.

TABLE I. EVALUATION METRIC VALUES OF THE TRAINED MODEL

S. No.	Evaluation Metric	Value
1	Precision	0.95
2	Recall	0.87
3	F1 Score	0.92
4	Accuracy	0.98



1. [[1.0000000e+00 6.8145600e-19 2.7904948e-14 0.0000000e+00]]
   Diagnosed with COVID-19!
2. [[0.000000e+00 1.000000e+00 4.488387e-34 0.000000e+00]]
   Diagnosed with Ground Glass Opacity!
3. [[1.8685872e-37 7.3012404e-07 9.9999928e-01 0.0000000e+00]]
   Healthy
4. [[0.0000000e+00 0.0000000e+00 5.6737674e-11 1.0000000e+00]]
   Diagnosed with Viral Pneumonia!

Figure 13. Output response of the model for four of the test set images.

Table I lists the values of evaluation metrics obtained for the trained model with test set images as inputs. Note that accuracy is not a monotonically increasing function with each epoch since the model uses Adam optimizer. Fig. 13 shows the output probabilities of softmax layer for four figures from the testing set each belonging to a different class. It is observed that the model successfully predicts the labels for all of these images. The first value corresponds to COVID-19, second maps to Ground Glass Opacity, third is for Normal and fourth value corresponds to Viral Pneumonia. Clearly, there is a large disparity between the probability of the correct label and other probabilities.

VI. Conclusion and Future Scope

With rapidly increasing number of COVID-19 cases each day, alternatives such as Radiography based diagnosis can aid in facilitating early treatment of such lethal disease resulting in improved clinical outcomes. This work proposed one such methods which leverages CNNs and classifies COVID-19 affected patients based on their chest X-ray images. However, it is advised to approach medical professionals for practical usage of this model. As part of our future work, we intend to localize (using Object Localization) the regions in the X-ray that are peculiar and differentiate COVID-19 disease from other similar-in-effect diseases. This can help medical researchers when they would be experimenting with various variants of COVID-19. We are also looking forward to building a web-based application that diagnoses COVID-19 in the cloud as the user inputs his/her chest x-ray image through a browser. The same approach of CNNs and Object localization can be applied to diagnose other diseases like Cancer and Alzheimer's using X-Ray and Computer Tomography and MRI scans.

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