Pneumonia and COVID-19 Classification Using VGG16 Architecture

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Abstract- Pneumonia ,a disease in the lungs, has been found to be one of the most pernicious of diseases and has been a major cause of death among children. This disease is predominantly caused by viruses, bacteria or fungi. COVID-19, however, a more novel disease and a form of pneumonia, has hit the world by storm by claiming a hefty amount of lives in the past few years. The primary focus of this paper is to provide aid to the medical infrastructure by providing an efficient and accurate Machine Learning model having its foundations upon Convolutional Neural Networks(CNN) which can help patients differentiate whether they have Pneumonia or COVID-19, based upon scanned copies of their chest X-Rays. Training of the model was done with the help of a dataset containing Chest X-Ray images available on Kaggle. We put forward this model with the help of VGG16,a form of a CNN model which implements 16 convolutional layers to achieve its results. The results obtained by the model signifies that Deep Learning can be used in detecting COVID-19 and Pneumonia, hence providing help to the medical system.

I. INTRODUCTION

Pneumonia has various agents which help in its spread, for example, bacteria, viruses and fungi. 14% of all fatalities in children under the age of five are caused by it, wherein 740,180 deaths were reported in 2019 in children of that age group, according to data provided by WHO. [1] If detected early, opportunities are available for quick treatment to avoid its harmful effects. While COVID-19, a kind of viral pneumonia, has been declared a pandemic by the World Health Organization for 2020. It is caused by the SARS-CoV-2 Virus and has had an impact upon 645,630,482 people and has led to 6,634,816 fatalities worldwide since 2020.[2] This tremendously contagious disease spreads through close contact with an infected human or even objects containing the droplets contaminated by the virus. The disease has had Millions of fatalities since 2020. Also, no specific medicine for the disease is available, hence the vaccination and early detection are the most important factors in the treatment of this disease.

This paper helps provide an accurate Convolutional Neural Network deep learning model which can help patients get medical help as soon as possible. This model has been trained to provide quick results, for example, in a matter of seconds, hence fulfilling its aim to provide early detection of the diseases. The size of the dataset has a direct impact on the model's accuracy. Larger the size of the dataset, the larger is the opportunity to achieve higher accuracy.

The purpose of this paper is to create a VGG16 model which has high recall values, validation, accuracy, F1 scores and low validation loss. All these are various metrics which help determine the accuracy of a machine-learning model. Statistically, it has been observed that analyzing Recall values is preferred to other metrics because of its ability to provide an estimate of the amount of false positives in any model.[8] The number of false negatives is one of the most important factors to be taken into account in the medical system because if the model makes a wrong prediction about the patient not having the disease, even though he/she is suffering from the same, it can prove to be detrimental for the patient. Hence, the model's primary focus is to achieve high Recall values and good F1 scores.

The paper has been divided into various sections and they are as follows:
Section 1: This part serves as the paper's introduction and explains the topic of the research as well as its motivations. This section gives a brief idea about the objective of the research.

Section 2: This section provides knowledge about the related work already occurred in this field.
Section 3: This section provides detailed methodology used in creating the model and also provides various flowcharts and diagrams which help understand the working in a brief, concise and an easy to understand manner.
Section 4: This section analyzes the results provided by the developed model
Section 5: This section provides the conclusion to the research and helps in finding the future scope of the research undertaken. This section also provides all the references taken while creating the paper.

II. RELATED WORK

For many years, research in the area of image classification has been active.

Makris et al.[12] improved a number of CNN models and contrasted how well they classified COVID-19, pneumonia, and regular pictures. In their analysis, with a 95.88% overall accuracy, VGG16 displayed the best result..

Khuzani et al. [13] used Texture, FFT, GLCM, and GLDM among other techniques to carry out the feature extraction procedure. Two hidden layers with 128 and 16 neurons each made up the multilayer network used in the study, along with a final classifier. The COVID-19, pneumonia, and normal categories all reach a 94% accuracy rate.

According to the aforementioned research, radiologists may experience less stress if new corona viruses are detected on radiological imaging using deep learning algorithms. Only a few models, however, ended up performing well despite different deep learning techniques being used by different researchers.

In this work, various deep learning models that have achieved outstanding COVID-19 identification outcomes are compared. We modified the existing model in light of the categorization criteria we utilised in this investigation (VGG16). These models have shown encouraging results with the COVID-19 classification as well as excellent outcomes in the detection of pneumonia.

In this work, we assessed COVID-19 X-ray and pneumonia using the same data and variables to determine the most effective model to differentiate between them. Also, in order to eliminate biases, the model has been trained and evaluated using COVID-19 and pneumonia CXR pictures from several datasets. The performance indicators and computing time of the models are then compared. The best model is selected for this categorization after careful analysis of the outcomes.

III. METHODOLOGY

The VGG16 CNN Deep Learning Model has been built up and it has been trained with the dataset available on Kaggle. Tensorflow, the most commonly used library for Deep learning has been used along with Keras, another neural network library. Our dataset included 6220 images. 26 epochs were used in order to increase the accuracy of the model.

- Datasets:

Pneumonia Chest X-rays
The dataset is broken up into three folders called "Train," "Test," and "Val," each of which has subfolders named "Pneumonia" and "Normal." 5,863 chest X-ray scans of children at the Guangzhou Women and Children's Medical Center between the ages of one and five make up the dataset. From retrospective clinical care cohorts, these pictures were chosen.

Fig-1: Pneumonia X-ray Dataset

- COVID-19 chest X-rays

The patients with COVID-19 infection, as well as those with MERS, SARS, and ARDS who have tested positive for the virus or who have a high likelihood of having it, are included in this dataset, together with their chest X-rays and CT scans. The information, which consists of 357 chest X-ray pictures, was acquired from hospitals, doctors, and public sources and made available to the general public.

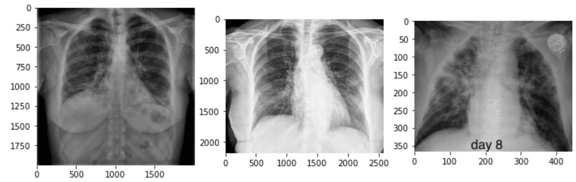


Fig-2: COVID-19 Positive X-ray Dataset

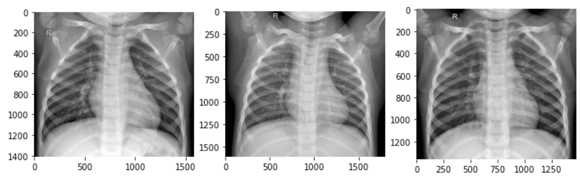


Fig-3: Normal chest X-ray Dataset

- Training on VGG16 Model:

VGG16 is a CNN based model trained on the ImageNet dataset. It was created by Oxford University's Visual Geometry Group (VGG). In the case of VGG16, there are a total of 16 layers, 13 of which are convolutional layers and 3 of which are fully linked layers. It is frequently used as the starting point for image recognition jobs.

The fully-connected layers of the network are responsible for using the features extracted by the convolutional layers to make predictions. These layers take the extracted features as input and use them to classify the input images into one of a predefined set of classes. In the case of VGG16, the model was trained on the ImageNet dataset, which contains a large number of images belonging to different classes, such as animals, objects, scenes, and so on. As a result, the VGG16 model is able to recognize a wide range of objects and scenes in images.

- CNN Architecture

Convolutional layers, pooling layers, flattening layers, and fully connected layers are just a few of the layers that CNN, a deep learning neural network, employs to do the necessary categorization.

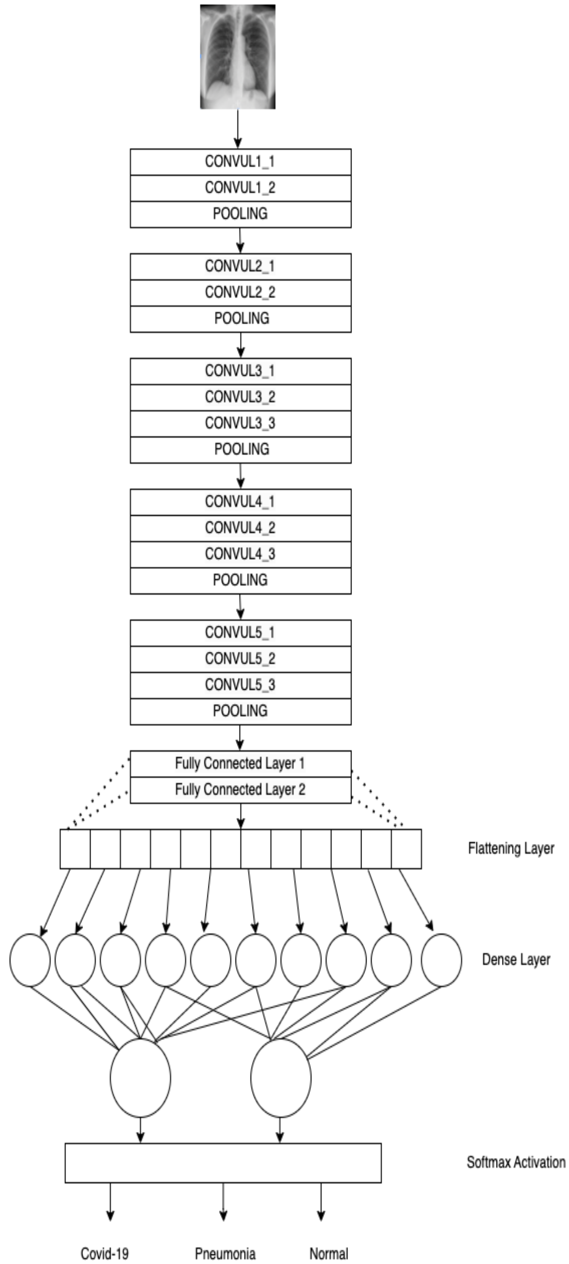


Fig-4: VGG16 Architecture used for prediction

- Convolutional Layer:

It is the most important component of the CNN architecture. It basically is a hive of convolutional filters(or kernels). It converts the input image into a feature map. And it achieves the same objective by doing element-wise multiplication through the filter and then recording the result as a matrix, also referred to as the feature map. If the input picture is in black and white, a 2D matrix is formed. If the input image is in color, the convolutions are created in 3D, with the RGB color representing the third dimension. With the help of multiple feature detectors, a layer of feature maps is generated and hence a convolutional layer is formed. [4]

- Pooling Layer:

The feature map subsamples are produced mostly by the pooling layer. These sub-samples are produced after the convolutional layer is built. This layer is also tasked with maintaining the dominant features in each of its steps. In convolution operation, the stride and kernel initially have specific values assigned to them before the operation is started. The same is the case here. [4]There are a plethora of pooling methods available to use, some of which are Min-pooling, Max-Pooling, Average Pooling, Tree Pooling, Global Average Pooling(GAP), and many more. However, the Min and the Max pooling are the ones very frequently used. The model created is using Max pooling technique since it retains most of the features, which is crucial to the prediction. [5]

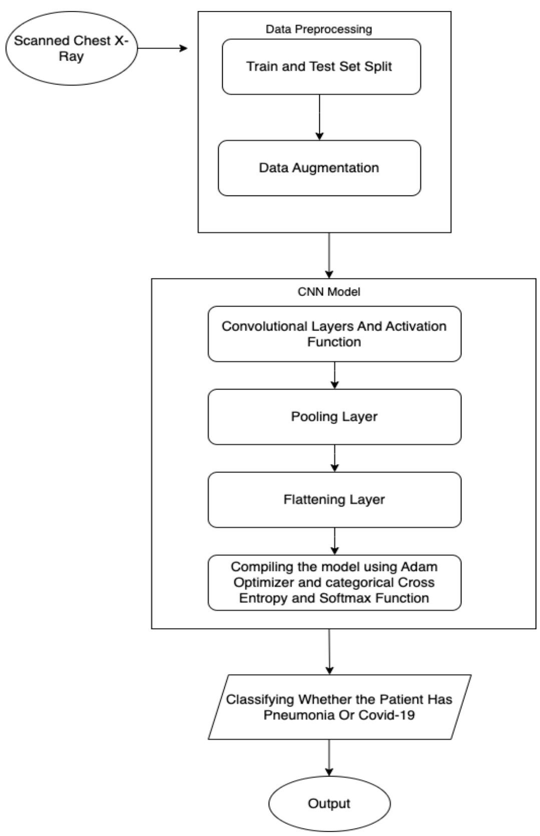


Fig-5: Flowchart Representing general CNN architecture

- Activation Function:

The Activation function, another important component of a neural network, is employed with the task of mapping the input with respect to the output. By producing the matching output, the activation function decides which neurons to activate in response to which inputs.. These activation functions help achieve non-linear performance, giving the CNN ability to differentiate more complicated features. The two main activation functions are the Softmax activation function and the ReLU activation function. Rectified Linear Function is the full name of the ReLU activation function. Multiple Variants of ReLU activation function are present, namely Leaky ReLU, Noisy ReLU, Parametric ReLU, and many more.The ReLU activation function converts whole values of the input provided with positive values. This leads to it having a lower computational load.

Softmax activation function, widely used in creating CNNs is used to create the input into a probability distribution.

- Fully Connected Layer and Flattening:

Near the end of the neural network is where the Fully Connected Layer is primarily located. [9] As a CNN Classifier, each neuron in this layer communicates with the neurons in the layer underneath it. However, before the fully connected layer operates on the input, a method known flattening occurs on the input wherein the complexities of the image are further reduced by flattening the input into a column. The fully connected layer receives this flattened input and uses each layer to extract features from the input and generate a prediction, which also serves as the final output for the CNN.

- Model training

Using a 12 GB NVIDIA Tesla K80 GPU, our deep learning model, VGG16, was trained. All of the photographs in the dataset were shrunk to 224 224 pixels. The CNN method was developed using the deep learning framework TensorFlow 2.4 with Keras API. The model was trained with the categorical cross-entropy loss function, and ground truth probabilities were used to assess the model's performance.

IV. MODEL PERFORMANCE

In order to analyze the performance of the model, there are various metrics available. We have chosen F1 Scores, Recall Values and Validation Accuracy as the performance measures for the same. The confusion matrix for the model was created and was used in finding the values of these metrics.

In the equations given below, we have taken T.p = true positive, R.p = false positive, T.n = true negative and R. n= false negative.

Accuracy = (T.p + T.n) ÷ (T.p + T.n + R.p + R.n)

Precision = T.p ÷ (T.p + R.p)

F1 Score = 2 × (Precision × Recall)
÷ (Precision + Recall)

Recall = T.p ÷ (T.p + R.n)

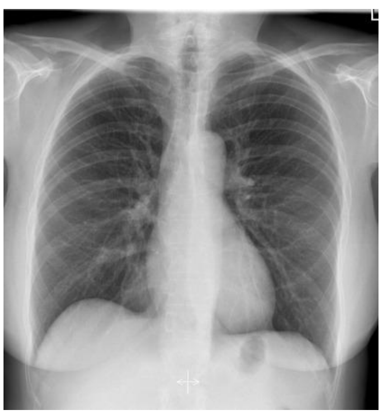


Fig-6: X-Ray sample of normal lungs.

Fig-7: X-Ray sample of Pneumonic Lungs

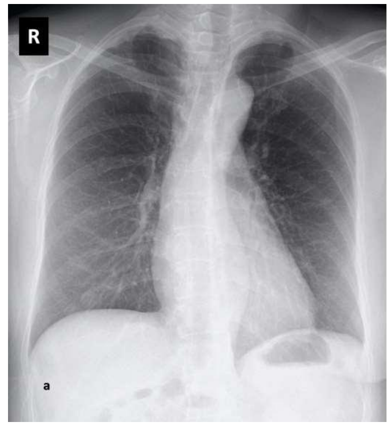


Fig-8: X-Ray sample of Lungs with COVID-19

- Experimental results:

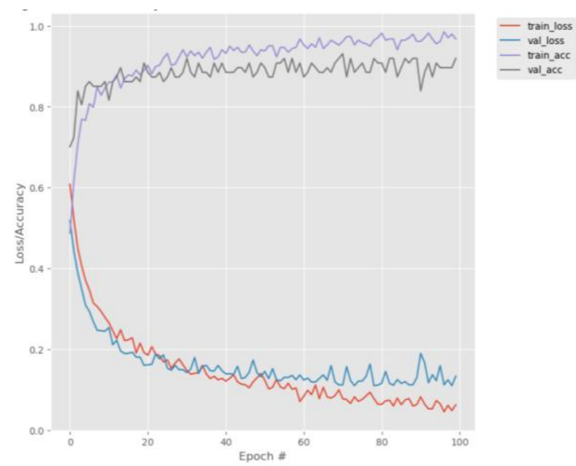


Fig-9: Training Loss and Classification Accuracy for Normal, COVID-19, and Pneumonia

In Table 1 and Fig. 9, respectively, are listed the accuracy and loss data from the training and validation procedure for our model. InceptionV3 and ResNet50 both attained a minimum validation loss after just 3, and 4 epochs, respectively, when comparing the number of epochs needed by each model to do this. With the fewest number of epochs conceivable, they can attain validation accuracy of 99% or higher. This suggests that these models can quickly pick up on the characteristics that set COVID-19 and pneumonia apart.

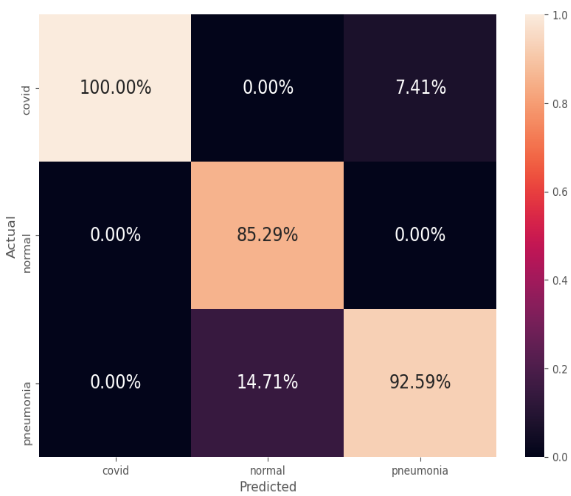
ResNet50 and VGG16 have the highest training accuracy and the lowest training loss, respectively, when accuracy and loss are considered.[10]

Inception-ResNet-V2, VGG16, and VGG19 all have higher accuracy for the validation set, but VGG16 has the lowest validation loss. [11]

Table-1:

Classifier Model	Precision	Recall	F1 Score	Support
COVID	100	93	96	28
Pneumonia	93	83	88	30
Normal	85	100	92	29
Weighted Average	93	92	92	87

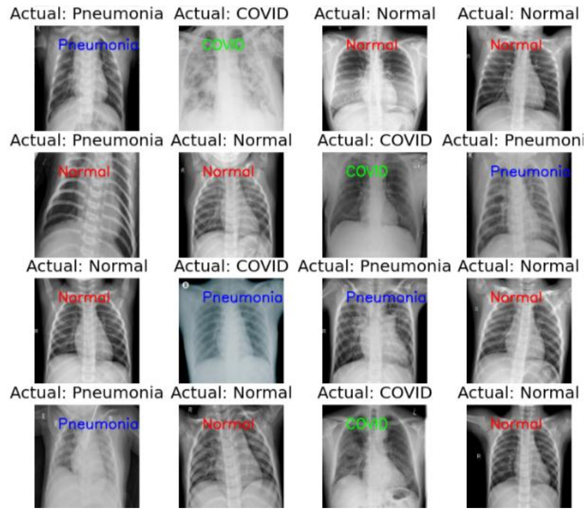
- Heat Map



These findings show that the VGG16 model outperforms the competition in terms of training and validation.

CONCLUSION

The F1 Score, Validation Accuracy, Precision and Recall values of the Model which includes 16 convolutional layers are 92 %, 96.75%, 93% and 92%, which are quite high.



Hence, with such high recall values, we can conclude that this model can be used by medical practitioners for diagnosing pneumonia and COVID-19 early in children as well as adults. A large amount of X-Rays can be processed by the model fairly easily and in a few seconds, thereby providing quick response. This convolutional neural network can hence help reduce mortality rate among the patients and help provide treatment as per the requirement of the patient

The deep learning models may have been able to recognise anything odd in the CXR images, which provides the deep networks the capacity to reliably identify the images, according to the high accuracy rates that were discovered. These trained models can greatly minimize the work of medical personnel while improving the accuracy and effectiveness of COVID-19 diagnostics.

In the future, it is hoped that further research on the same would lead to even more accurate predictions than the ones mentioned.

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