Coronavirus and Pneumonia Detection from X-Ray Images Harnessing Deep Learning and Transfer Learning Techniques

Abstract— **COVID-19 has been spreading quickly across the globe. Some extreme cases have been seen where patients experience the ill effects of pneumonia with coronavirus. COVID-19 along with pneumonia is a serious illness that can be deadly. In this study, our goal is the classification of COVID-19 from COVID-19 with Pneumonia using X-ray. We used the VGG-16 model, which is pre-trained for image classification on a dataset of over 14 million images belonging to 1000 classes. The model developed in this study achieved top-5 test accuracy of 92.7% in ImageNet. In our approach, we load VGG-16 with chopped top layers. The last dense layers were chopped and fine-tuning is done after keeping already learned weights as initial parameters. We were able to record 96% top-2 accuracy on the finely tuned model.**

Keywords—**COVID-19, Deep Learning, Transfer Learning, Logistic Regression, VGG-16**

I. INTRODUCTION

The spread of the global pandemic started from Hubei (also named as Hupeh) the landlocked province of the People's Republic of China and has now infected almost the entire world. The WHO Emergency Committee declared a global pandemic on 30th January 2020 based on a sudden spike in cases all around the globe. Patients infected with COVID-19 generally show symptoms of fever, cough, difficulty while breathing, and muscle aches. COVID-19 pneumonia is a specific disease, whose peculiar symptoms are headaches, restlessness and shortness of breath. Patients suffer due to low levels of oxygen in the blood[1].

COVID-19 is a family of viruses called Coronaviridae that infects humans along with various animal species also. The method used to detect the presence of the virus among humans is the real-time-reverse-transcription polymerase chain reaction (RT-PCR) test. The specimens obtained via nasopharyngeal swab, tracheal aspirate, bronchoalveolar lavage or oropharyngeal swab helps us identify the presence of viral nucleotides. Recently, it has been observed that RT-PCR has sensitivity as low as 60-71% for aiding the COVID-19 detection. This might be a reason for the laboratory error or the low viral load present in collected specimens. Increased false negatives can cause the spread of disease at a mass level. This also increases the chances of redundant testing and can thus overload the medical infrastructure available within countries.

In some serious cases, patients suffer from pneumonia along with other common symptoms of COVID-19. It has been observed that a chest X-ray can be used to detect pneumonia in patients who are COVID-19 positive. Machine learning models used with radiological images can accurately detect this disease. This can likewise beat the absence of specific doctors in far off locations.

In our research, we engineer a COVID-19 Pneumonia detection model using Deep and Transfer Learning techniques. A comprehensive dataset containing X-Ray images from Kaggle is employed. The model uses VGG-16. VGG-16 is pre-trained for image classification on a dataset of about 14 million samples that belong to over 1000 classes. Further, a new layer of logistic regression is applied to the previous pre-trained VGG-16 model and the resulting model is used on the dataset.

II. RELATED WORK

Transfer learning can be described as a machine learning technique that was inspired by the human ability to intelligently apply the wisdom gained from one task to solve problems in another task with a better approach. The idea of transfer learning was initially analysed in the NIPS-95 workshop on "Learning to Learn"[2]. It was mainly focused on the need for enduring machine learning models that can store and further use the knowledge gained from other tasks.

Benbrahim, Hachimi, and Amine identified the virus using a blend of Logistic Regression, Spark and Tensorflow by utilizing chest CT images[3]. They acquired a classification accuracy of 85.64, 84.25, and 82.87%, for VGG-16, VGG-19, and Xception.

Wang et al[4] proposed a tailored architecture of CNN to detect COVID-19 images. The COVID-net architecture aimed to classify the images into 3 categories: covid pneumonia, and no findings. They were able to achieve overall accuracy of 92.4% with 80% sensitivity for COVID-19.

Luz et al.[5] employed a lightweight implementation of a COVID-19 classifier. They used a flat version of the EfficientNet backbone and reported an accuracy of 93.9%, COVID-19 Sensitivity of 96.8%. Khalifa et al.[6] proposed a Generative Adversarial Network-based adjusted model for identifying pneumonia from ChestX-Ray samples, which is one of the symptoms of COVID-19 disease. Apostolopoulos and partners apply transfer learning[7] examining 224 COVID-19, 700 pneumonia, and 504 ordinary samples. They arrive at a precision equivalent to 0.98 in the COVID-19 and sound segregation. Multi-Channel TL-based strategy with X-Ray samples has been proposed in[7]. This study[9] is restricted to some particular HDA errands since they required extra data to move the source information to the objective space.

III. DATASET

For our study, Chest X-Ray images were obtained from the Kaggle for COVID-19 Pneumonia classification. The dataset contains 289 image samples of people with COVID-19 along with Pneumonia and 242 image samples of people with COVID-19 without Pneumonia. Further, the dataset was split into 386, 81 and 64 images for training, validation and evaluation purposes respectively [10]. Figures 1 & 2 are chest X-ray images of COVID-19 with Pneumonia and Covid 19 without Pneumonia respectively

Figure 1: COVID-19 with Pneumonia

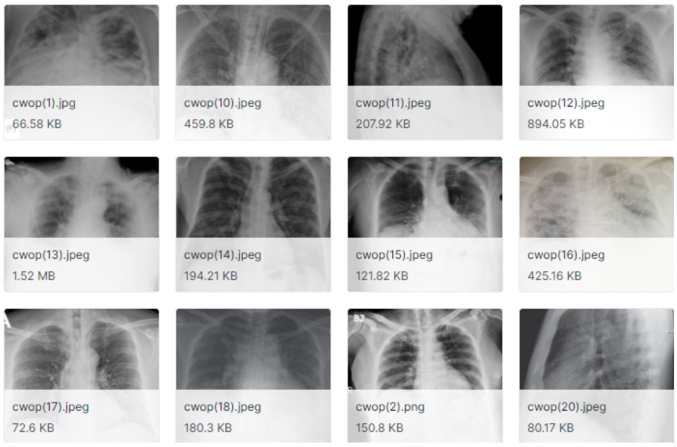

Figure 2: COVID-19 without Pneumonia

IV. PROPOSED FRAMEWORK

The proposed model has two principle segments, the first segment is deep transfer learning; where we utilise one of the models, VGG-16, as a feature extractor and the subsequent segment is a classic machine learning algorithm, Logistic Regression which is used to classify the images and check accuracy for training and validation data. The proposed model helps us to overcome the limited data constraint which is a common phenomenon when dealing with the medical field.

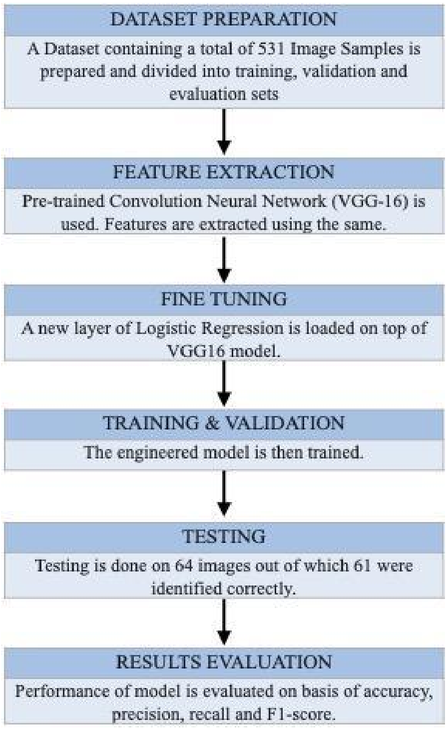

Figure 3: Proposed Framework

A. Transfer Learning

In its most easy definition, transfer learning can be explained as the application of wisdom gained by one model into another model. It has been observed that many deep neural networks learn similar low-level features on natural images. Low-level features are information related to corners, texture, edges and colour blobs which are recorded in the initial layers of a CNN model. These low-level features apply to other datasets and tasks too. Transfer learning can be best utilised in scenarios where the training samples are limited like medical images.

Through transfer learning, we look forward to improving the prediction ability of a target task, using the knowledge gained from a source project. Here the source and target domain need not be similar.

B. Convolutional Neural Network

Convolutional Neural Network utilises various perceptrons to investigate input images and then learn weights and bases of a few pieces of pictures and are ready to isolate one another. One benefit of using a CNN is that it utilises the use of local spatial coherence in the input pictures, which permits them to have less weight as certain boundaries are shared. This process is effective as far as memory and intricacy. The fundamental structure squares of convolutional neural networks are:

a. Convolution Layer - A convolutional layer is a primary layer that performs convolution operation on the image using a Kernel matrix. We aim to find dot products by sliding the Kernel matrix over the previously created matrix of the input image. In each step, the convolution operation is performed to create a feature map that provides information about corners and edges. The feature map created is used as input for the next layer. Convolution is a specific sort of linear operation which is broadly utilized in a variety of domains including image processing, statistics, physics. Convolution can be applied over more than a single axis. On the off chance that we have a piece of 2-Dimensional picture information, I, and a 2-Dimensional kernel filter, K, the resulting image is calculated using the following:

$$S(i,j)= \sum\sum I(m,n)k(i-m,j-n)$$

b. Non-Linear activation functions (ReLU) - After each CONV Layer in a CNN, a non-linear activation function is applied.

Activation layers are denoted as (rectified linear unit activation function) ReLU in network diagrams as they are most commonly used. ReLU is a piecewise linear function that will yield the info if it is positive, else, it will yield zero.

c. Pooling Layer - A major issue with the output of feature maps in a layer of CNN model is that it records the exact location of features in dataset images. This implies that with any change in the data, the image will bring about a different feature map. To conquer this issue, feature maps are downsampled. Downsampling can be accomplished by applying a pooling layer after the nonlinearity layer. Pooling helps in reducing the effect of small translations of the input. Invariance to translation implies that on the off chance that we decipher the contribution just barely, the upsides of the vast majority of the pooled yields don't change.

d. Fully Connected Layer - Towards the extremity of a CNN, the result of the last Pooling Layer goes as the input for the Fully Connected Layer. More than one of these layers is possible. Fully connected implies that every node in the initial layer is connected to every node in the second layer.

VGG-16

Visual Geometry Group is a convolutional neural net (CNN). The significant characteristic of this architecture focuses on simple 3 x 3 size kernels in convolutional layers and 2 x 2 in max-pooling layers, in place of the large number of hyper-parameters.

All in all, it has 2 fully connected layers followed by a softmax layer for output. The most conventional VGG models are VGG-16 & VGG-19 which consist of 16 & 19 layers respectively.

In our study, the utilised model is only till the final max pool layer in the VGG-16 architecture.

The extracted features from the VGG-16's final max-pooling are used as an input for a Shallow Neural Network. This can also be termed as Transfer Learning along with Feature Extraction.

C. Logistic Regression

Logistic Regression is a mathematical model which enables the probability estimation of belonging to a certain class. Logistic Regression can be of various types: Binary LR and Multinomial LR. In this paper, the former one is used.

We employ the flattened extracted features from VGG 16's last max-pooling layer. The extracted features are then used as input to the Logistic Regression Classifier. Further, we use the validation set to fine-tune the hyperparameters of our LR model. It is observed that the regular LR model performs better than the default LR model.

V. RESULT ANALYSIS

Our models beat the previously recorded accuracy scores achieving top-2 accuracy of 98% indicating strong differentiation abilities between pneumonia and covid images. The model was able to correctly identify 63 images. As only an accuracy based performance indicator is not enough to validate an optimal classifier.

We have evaluated the performance of our model on basis of the following metrics:

$$Precision = TP / (TP + FP)$$

Recorded a precision of 0.98.

$$Accuracy = (TP + FN) / (TN + TP + FN + FP)$$

Recorded accuracy on model is 0.98

$$F1 = 2 * ((Recall * Precision) / (Recall + Precision$$

The F1 score for the model was 0.97.

Here,

$TP = True\ Positive,\ TN = True\ Negative$

$FP = False\ Positive,\ FN = False\ Negative$

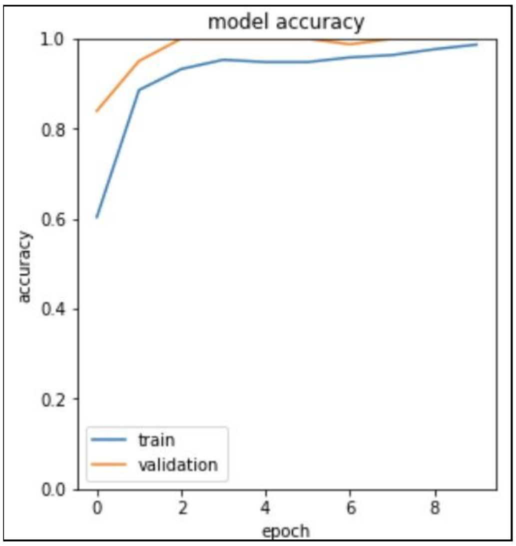

Figure 4: Plot for Accuracy

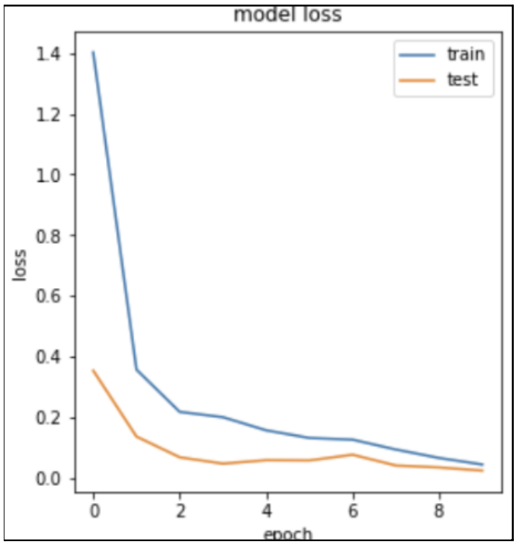

Figure 5: Plot for Loss

VI. CONCLUSIONS

In this work, we have presented automated methods used to do the binary classification of chest X-rays images into COVID with pneumonia and COVID without Pneumonia using the VGG-16 model coupled with the Logistic Regression model. The experiment was conducted using 531 X-ray images and performance was evaluated using performance indicators such as accuracy, precision, F1-score. The model was able to achieve good results in terms of accuracy irrespective of a small dataset. We were able to use weights learned from previous tasks in the target task. After extensive experiments on datasets, it is shown that the proposed model predicts COVID-19 pneumonia diagnosis with high accuracy of 96% and very low false negatives. This has been a significant improvement on state of art models as per the best of our knowledge.

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