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Classification of Chest Radiographs for Detection of COVID-19 Using Convolutional Neural Networks

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ABSTRACT: A novel coronavirus also unknown as COVID-19 was identified which was not known to humankind. The infection can be transformed from one person to the other through direct contact with the infected person or by touching the surfaces where the virus is present. The outbreak started to spread across many countries and it was declared as global pandemic in March 11 2020 by World Health Organization (WHO). The fast spread of the pandemic put an unprecedented overload on the health care system. Due to limited test kits and resources, the early diagnosis of the infection was an immediate problem. One of the ways the infection can be detected is by examining the patient's lung condition by taking chest X-ray images. Detection of the infection and classifying it among other images like healthy lungs and viral pneumonia is of vital importance for both doctors and patients to decrease the diagnostic time and reduce the financial costs. In this paper, we have built a Convolutional Neural Network model for classification of chest X-ray images into COVID-19, Normal/Healthy and Viral Pneumonia classes. A publicly available dataset has been taken for the training of the model. The dataset is split into training and testing sets. The training set is further divided into 80% training and 20% validation. The dataset is pre-processed with scaling factor = 1./255 and all images were resized to 350 x 350 pixel size in the dataset. We have trained the model with 20 number of epochs with early stop callbacks. Rectified Linear (ReLU) activation function is used in the training with softmax activation function for the output layer. We have used Categorical crossentropy as our loss function for multiclass problem. The proposed model has achieved training accuracy of 99.58% and validation accuracy of 90.83%.

KEYWORDS: COVID-19, Viral Pneumonia, Chest Radiographs, Convolutional Neural Network

I. INTRODUCTION

A novel coronavirus also known as COVID-19 was identified at the end of 2019 in Wuhan, China which was not known to humankind. Coronaviruses are a wide sort of viruses that causes common cold in humans and in some severe cases it can cause diseases like Middle East respiratory syndrome and severe acute respiratory syndrome. The infection can be transformed from one person to another through direct contact with respiratory droplets or aerosols of an infected person which is generated through sneezing or coughing typically within the short range of 1 metre. A person can also be infected with touching the surfaces where the virus is present and touching the nose, eyes or mouth. Because of the possibility of easy spread of the infection, the World Health Organization (WHO) declared the outbreak as a Public Health Emergency of International Concern on 30 January 2020. Soon enough the outbreak started to spread in many other countries and the WHO declared it as a global pandemic on 11 March 2020. The fast spread of the virus put an unprecedented overloaded on health care system when people did not expect it. In mild cases, the infection ends with cough and fever. But in some severe cases like less than 2 in 10 cases people faced difficulty in breathing. People infected are required to be in isolation and monitor their oxygen level. If oxygen level drops and the patient face difficulty in breathing, the patient is required to contact a medical authority. Health care workers including doctors, nurses, pharmacists play an important role in this pandemic.

The sudden spike in the number of infected people across the world has put an unprecedented load on healthcare systems. In many countries, the healthcare system has been overwhelmed with limited personal protective equipment (PPE) and limited beds for severely infected people. The only way to tackle the situation is to test as many people as possible in the early stages. There are several ways to detect COVID-19, few among them are Polymerase Chain Reaction (PCR) tests, Lateral Flow Tests (LFTs), Chest CT (computed tomography) scans and Chest x-ray scans. One technique has advantages over the other. PCR tests are sent away to a laboratory to diagnose disease, whereas LFTs can diagnose COVID-19 on the spot but it is not as accurate as PCR. Although some countries have limited test kits, they

can go for chest scan to detect COVID-19 infection in patient's lungs. COVID-19 diagnosis can be performed by taking chest scan of the patient to examine the lung condition, if the patient shows pneumonia in the scans, they are considered to be tested positive. The early diagnosis of the infection allows doctors to isolate and treat the patient in timely manner.

The financial costs of PPEs, test kits, and CT (computed tomography) used for diagnosis, especially for underdeveloped and developing countries is an issue when fighting this pandemic. It is recommended to use chest radiography for detection of COVID-19 in patients where there is a limitation for test kits or access to CT. X-ray is an imaging technique to detect bone fractures, displacement, tumour and pneumonia. Hence it can be a useful tool in the detection of COVID-19 infections. X-rays are capable of generating chest images that show lung damage such as pneumonia caused by the virus. X-rays are less harmful, faster and cheaper compared to CT scans. Furthermore, X-ray devices are portable and can be easily transported to wherever needed.

II. RELATED WORK

In [1] authors propose a solution to automatically classify COVID-19 cases in chest x-ray images. The ResNet-101 architecture with more than 44 million parameters was adopted as the main network. Large size of 1500×1500 x-ray images were used to train the whole network. In each input x-ray image, the heatmap under the region of interest of segmented lung is constructed to visualize signals of COVID-19. Using the pretrained U-Net lungs are segmented. For each classification result the confidence score of being COVID-19 is also calculated. The proposed solution is evaluated based on normal and COVID-19 cases. The model is also tested on some unseen classes to validate a regularization of the constructed model. The unseen classes include other abnormal cases where chest x-ray images are abnormal with some diseases containing remarks similar to COVID-19 and other normal cases where chest x-ray images are normal with no disease but with some small remarks. The proposed method can achieve the accuracy, specificity, and sensitivity of 98%, 98%, and 97%, respectively. It was concluded that the proposed model can detect COVID-19 in a chest radiography image. For users or human experts use for a final diagnosis in practical usages, the heatmap and confidence score of the detection are also demonstrated.

In [2] it presents CovidAID: COVID-19 AI Detector is a novel deep neural network-based model to detect COVID-19 infection in patient's using chest x-ray. On the publicly available COVID-19 Chest x-ray dataset, this proposed model gives 90.5% accuracy with 100% sensitivity (recall) for the COVID-19 infection. They significantly improve upon the results of Covid-Net on the same dataset. The Covid-Net model contains pre-trained CheXNet, with a 121-layer Dense Convolutional Network backbone, followed by a fully connected layer. They have replaced CheXNet's final classifier of 14 classes with their classification layer of 4 classes, each with a sigmoid activation to produce the final output. The results of the proposed model indicate that this approach can lead to COVID-19 detection from x-ray images with an Area under ROC curve of 0.9994 for the COVID-19 positive class, with a mean AUROC of 0.9738. Authors plan to further validate the proposed model using larger COVID-19 chest x-ray image datasets and clinical trials.

In [3] Deep learning is the most popular technique of machine learning, which is used to study a large amount of chest x-ray images that can help with screening of COVID-19. In this work, they have taken the posteroanterior (PA) view of chest x-ray scans for covid-19 affected patients as well as normal chest x-ray scans for healthy patients. In the first step, they have used data pre-processing and applied data augmentation. They have used several deep learning-based CNN models and compared their performance to evaluate the best model. They have compared Inception V3, ResNeXt, and Xception models and examined their accuracy. To analyse the model performance, 6432 chest x-ray images have been collected from the Kaggle repository, and it is split into 5467 images for training and 965 images for validation. In result analysis, the Xception model gives the highest accuracy of 97.97% for detecting Chest X-rays images with comparison to other models. This work only focuses on possible methods of classifying covid-19 infected chest x-ray scans and the authors do not claim any medical accuracy. In the future work, we can validate the proposed model on large dataset for chest x-rays.

In [4] Detection of COVID-19 from chest x-ray images is very important for both patients and doctors to reduce financial costs and decrease the diagnostic time. Some of the methods that can be used for this task are Artificial intelligence, deep learning and Convolutional Neural Networks which are capable of recognizing images and classify them. In this study, the authors have performed several experiments for detection of COVID-19 in chest X-ray images using ConvNets with high accuracy. Various groups of datasets like COVID-19/Normal, COVID-19/Pneumonia, and COVID-19/Pneumonia/Normal were considered for the classification. Different network architectures, different image

dimensions, state-of-the-art pre-trained networks, and machine learning models were implemented and evaluated using images and statistical data. The considered architectures reduce the computational cost with high performance when the number of images in the database and the detection time of COVID-19 are considered using ConvNets. The average testing time for detection of COVID-19 is 0.03 seconds per image. In this paper, the result shows that the convolutional neural network with minimized convolutional and fully connected layers is capable of detecting COVID-19 images within the two-class, COVID-19/Normal and COVID-19/Pneumonia classifications, with mean ROC AUC scores of 96.51 for COVID-19/Normal and 96.33% for COVID-19/Pneumonia. In addition, they have proposed a second architecture, which had the second-lightest architecture. It is capable of detecting COVID-19 in three-class which are COVID-19, Pneumonia and Normal images, with a macro-averaged F1 score of 94.10%. Hence it was concluded that the use of AI-based automated high-accuracy technologies may provide valuable assistance to doctors in diagnosing COVID-19 and reduce diagnostic time. The future scope of the study is to provide more information about CNN architecture and its use with COVID-19 chest x-ray images and improve on the results.

In [5] the authors have suggested a novel COVID-19 detection in chest x-ray technique based on the locality-weighted learning and self-organization map (LWL-SOM) strategy. They first grouped images from chest x-ray datasets based on their similar features in different clusters using the SOM strategy in order to discriminate between the COVID-19 and Normal cases. Then, they built an intelligent learning model based on the LWL algorithm to diagnose and detect COVID-19 cases. The proposed LWL-SOM model improved the correlation coefficient performance results between the Covid19, no-finding, and pneumonia cases from 0.9613 to 0.9788; pneumonia and no-finding cases from 0.6113 to 1; Covid19 and pneumonia cases from 0.8783 to 0.999; and Covid19 and no-finding cases from 0.8894 to 1. The proposed LWL-SOM had better results for classifying COVID-19 and Normal patients than the existing machine learning-based solutions which uses AI evaluation measures. The locality-weighted learning algorithm has been adapted by adding a clustering process to the dataset before using the LWL, which is called the LWL-SOM model for the detection of COVID-19 cases from chest x-ray findings. The diversity and similarity of these clusters is highlighted in the dataset instances, consequently helping to identify variations among classes of the dataset and facilitating the classification and learning process when constructing the LWL diagnostic model. Radiological imaging method is used to emphasize the performance of chest X-rays with different type of cases such as positive COVID-19, Normal, and pneumonia cases.

III. MATERIALS AND METHODS

A. Dataset

The dataset has been collected from Kaggle repository, a team of researchers from Qatar University, Qatar, and the University of Dhaka, Bangladesh along with their collaborators from Malaysia and Pakistan in collaboration with medical doctors have created this database of chest x-ray images for COVID-19 positive cases along with Normal chest x-ray and Viral Pneumonia chest x-ray images. In the first stage, they had released 219 Covid-19, 1341 normal, and 1345 viral pneumonia chest x-ray images. In the second stage, they increased the Covid-19 class to 1200 chest x-ray images. In the third stage, they have increased the database to 3616 Covid-19 positive cases along with 10,192 Normal, 6012 Lung Opacity (Non-COVID lung infection), and 1345 Viral Pneumonia images. In this study, we have used 1000 images with confirmed Covid-19, 1000 images with confirmed Viral Pneumonia and 1000 images of normal condition. Figure 1 shows the number of images per class and figure 2 shows the samples of each class. The dataset is further divided into 80% training set and 20% validation set. The data pre-processing is performed on the dataset with scaling factor = 1./255 and all images were resized to 350 x 350 pixel size in the dataset.

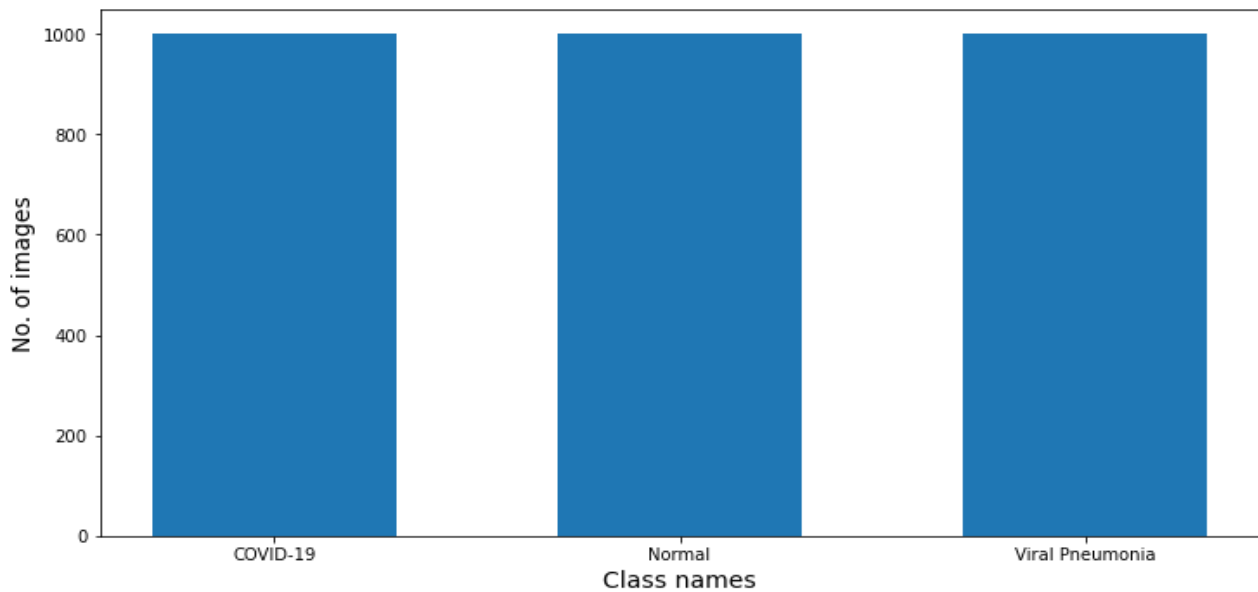


Figure 1: Number of images per class

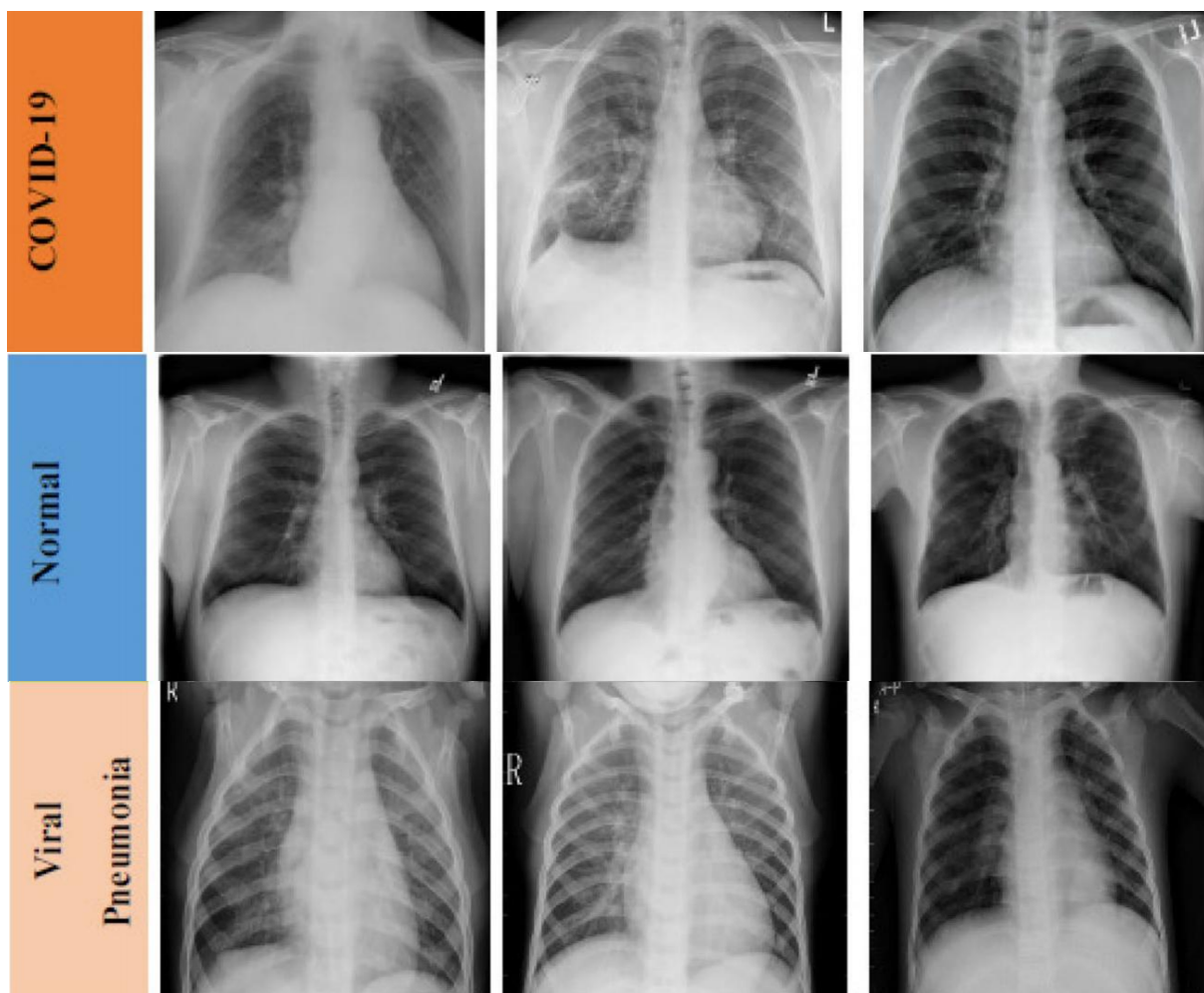


Figure 2: Representative chest X-ray images of COVID-19 (first row), Normal/Healthy lung (second row) and Viral Pneumonia (third row) patients.

B. Architecture of Convolutional Neural Network:

Deep learning is a sub-branch of machine learning that imitates the workings of human brain in processing data and recognising patterns for use in decision making. Deep learning has shown super human accuracy in image classification, image segmentation and object detection. In recent years deep learning techniques has shown impressive performance in medical image processing as in many other fields. By applying deep learning techniques to medical data, we can obtain meaningful results from medical data. Deep learning applications have been seen in medical imaging solutions, identifying specific types of cancer, and rare diseases of specific type. Analysis of signal data and image obtained with medical imaging techniques such as X-ray, magnetic resonance imaging (MRI), and computed tomography (CT) with the help of deep learning models. As a result of these analyses, detection and diagnosis of diseases such as tumour, skin cancer and breast cancer can be detected. Deep learning can be further classified into Supervised learning and Unsupervised learning. Supervised learning refers to the problem where the target to be predicted is clearly labelled within the dataset that is used for training. One of the most popular supervised deep learning architectures is Convolutional Neural Network (CNN). It is mainly used for image recognition problems. The CNN architecture is made up of several layers that implement feature extraction and then classification. In the first stage the images are converted to matrix format because the input must be recognised by computers and converted into a format that can be processed. The model determines which image belongs to which label based on the differences in images or the matrices. The model will learn the effects of these differences on the label during the training phase and then we can make predictions for new images using them. CNN consists of three different layer and any number of hidden layers. The primary layers of CNN are convolutional layer, pooling layer, and fully connected layer. The feature extraction takes place in the first layer that is convolutional layer. In the pooling layer the dimensionality of the extracted features is reduced while retaining the most important information which is typically done by max pooling. Another convolutional and pooling step in performed and the output is fed into fully connected layer. The classification process occurs in fully connected layer. The architecture of CNN is shown in figure 3:

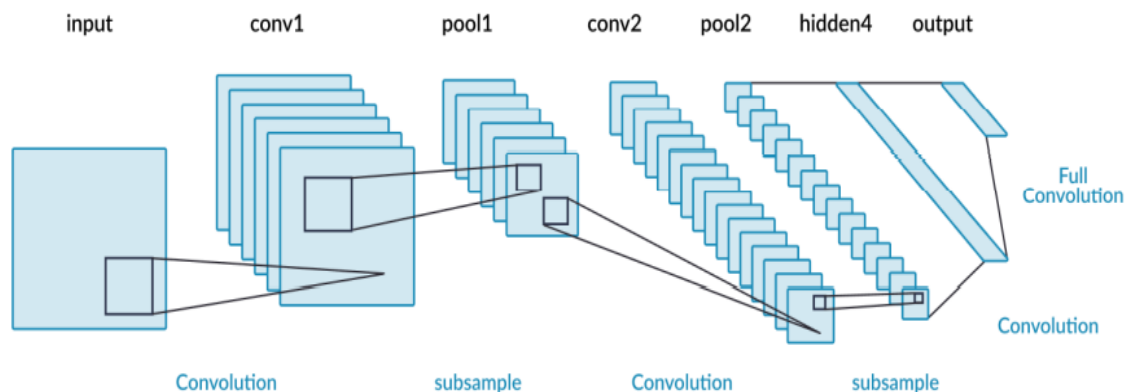


Figure 3: Architecture of Convolutional Neural Network

C. Loss function used: Categorical cross-entropy

To train our model we have used the categorical cross-entropy loss. The loss function is used to optimize the parameters used in our model. We expect to decrease the loss function with successive epochs. For training our model we have used adam optimizer with a learning rate = 0.001.

D. Activation functions used: ReLU and softmax

To help decide whether a neuron would fire or not we use activation function. An activation function is a node that is put at the end or in the middle of the neural network. We have used ReLU and softmax activation functions in the proposed method. ReLU function is the most used activation function which has an advantage over other functions because it does not activate all the neurons at the same time. It converts all the negative inputs to zero and the neuron does not get activated. While softmax is used as the last activation function to predict the output class in multi class classification problems.

IV. PSEUDO CODE

The algorithm used for implementing the proposed model is discussed below:

Step 1: Pre-process image i.e., image = X

For pre-processing we have used Data generator from Keras. Dataset is pre-processed with scaling factor = 1./255 and all images were resized to 350 x 350 pixel size in the dataset.

Step 2: Input layer

Apply the image to an input of the training model

Step 3: Convolve block

Apply max pooling with pool size (2,2) and strides

Step 4: Apply Flatten()

Flatten dimensions with reducing n dimensions to n-1.

Step 5: Apply dense layer

Units 120 and units 60, $Z = W*A+b$

Step 6: Apply activation function

ReLU is the activation function used here, $A = \text{ReLU}(Z)$

Step 7: Apply Dense layer for interference

Units 3 for classification of 3 different classes

$Z = W*A+b$

Step 8: Apply softmax for classification

V. RESULTS

In this section, we discuss the results achieved by our Convolutional Neural Network model. The primary goal of our approach was to correctly diagnose COVID-19 among Normal and Viral Pneumonia chest X-ray images. The system infrastructure used to perform training and testing was an Intel core i5 10th generation, 8 GB of RAM, with Windows 10 system without a graphical processing unit (GPU). In the training and testing processes, each individual image is fed into the Convolutional Neural Network model as the input at a time. Images from the dataset is independently split into two subsets of training and testing sets. The training set is further divided into 80% training set and 20% validation set, in each epoch of the CNN training phase. With successive epochs we aim to decrease the loss and increase the accuracy. Figure 4 shows the training loss of our model as it reduces with the consecutive epochs, x-axis shows the number of epochs and y-axis shows the loss. Figure 5 shows the training accuracy of our model as it improves with the successive epochs, x-axis shows the number of epochs and y-axis shows the accuracy. The model has obtained an accuracy of 99.58% for training and 90.83% for validation. The model has been tested on a testing dataset of unseen data, which consists of 100 chest x-ray images for each class. The confusion matrix on the test data is shown in figure 6.

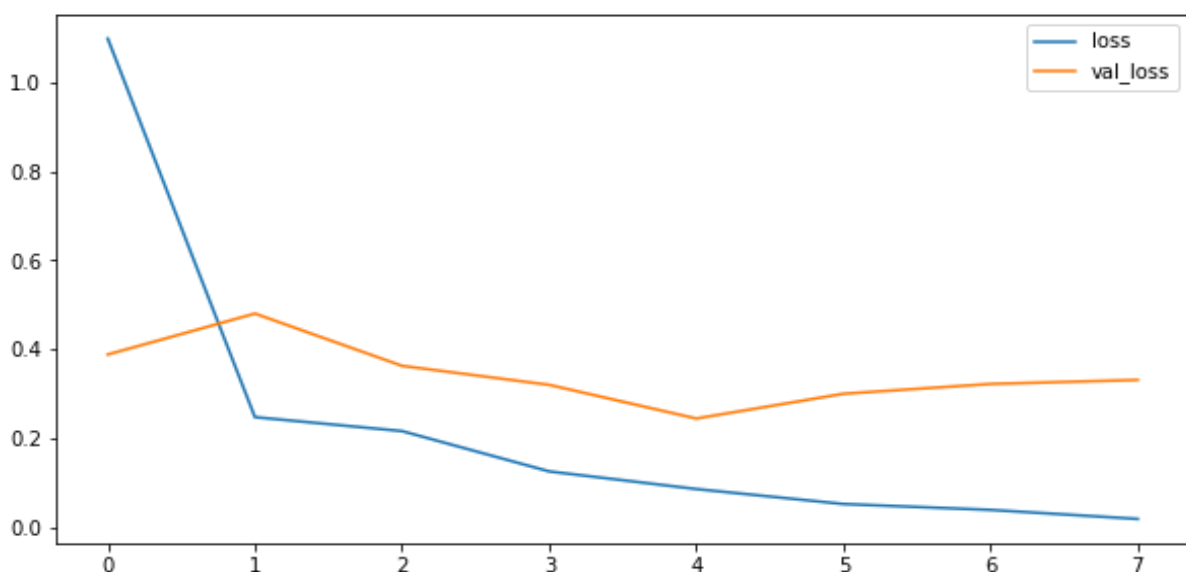


Figure 4: Training and Validation loss of the model

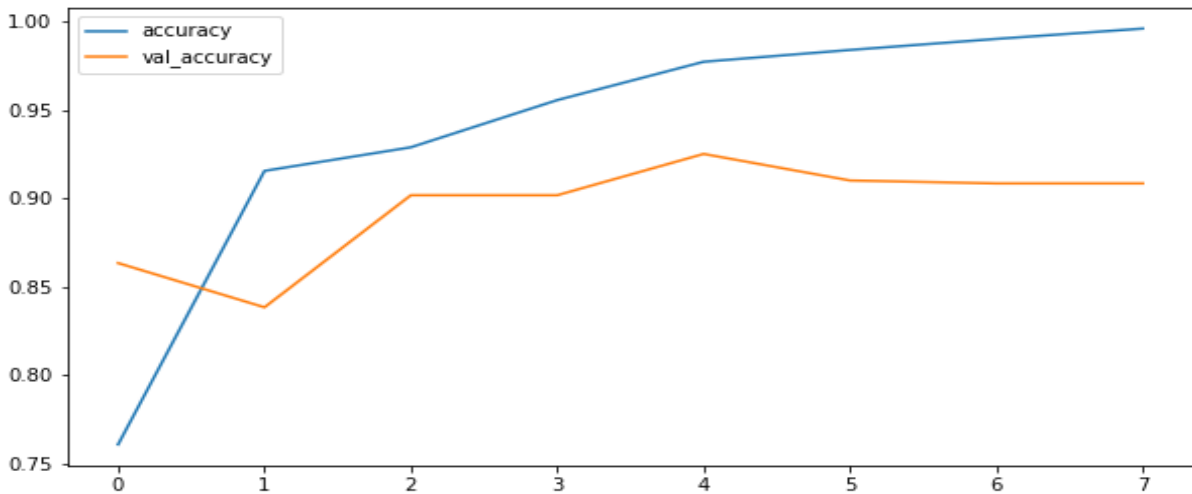


Figure 5: Training and Validation accuracy of the model

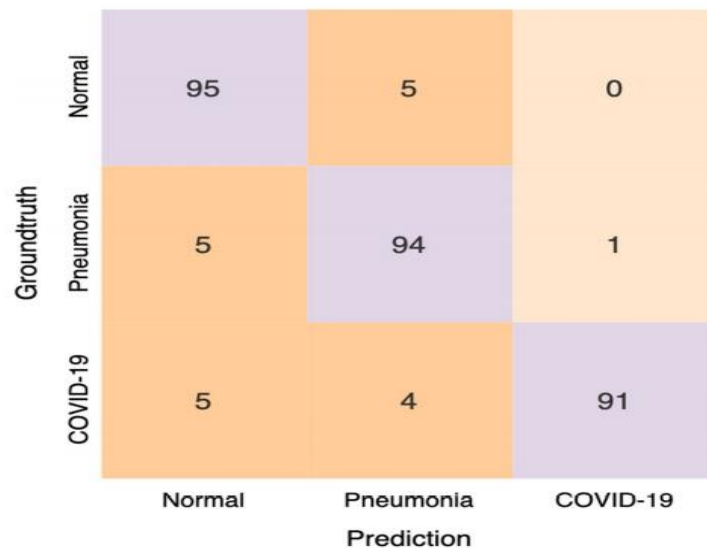


Figure 6: Confusion matrix of test data

VI. CONCLUSION AND FUTURE WORK

A novel coronavirus was identified at the end of 2019 in Wuhan, China and the infection can be transferred from one person to the other. The outbreak started to spread across many countries and it was declared as global pandemic in March 11 2020 by World Health Organisation (WHO). The fast spread of the virus put an unprecedented overload on the health care system in many countries. Due to limited test kits and resources, the early diagnosis of the infection was an immediate problem. One of the ways the infection can be detected is by examining the patient’s lung condition by taking chest X-ray images. Detection of the infection and classifying it among other images like healthy lungs and viral pneumonia is of vital importance for both doctors and patients to decrease the diagnostic time and reduce the financial costs. Artificial intelligence and Deep Learning are capable of images for the task required. In this study, we have built a Convolutional Neural Network model for classification of chest X-ray images into COVID-19, Normal/Healthy and Viral Pneumonia classes. A publicly available dataset has been taken for the training of the model. The dataset is split into training and testing sets. The training set is further divided into 80% training and 20% validation. The dataset is pre-processed with scaling factor = 1./255 and all images were resized to 350 x 350 pixel size in the dataset. The proposed model has achieved training accuracy of 99.58% and validation accuracy of 90.83%. Hence, the use of AI-based automated high accuracy technologies may provide valuable assistance for doctors in detection of COVID-19.

In the future work, we intend to increase the size of the dataset by adding new chest x-Ray images. Besides, we aim to test the model using an imbalanced dataset. We also intend to increase the pixel size of the images in the dataset to achieve better accuracy.

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