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Pneumonia Detection in Covid-19 Patients using CNN Algorithm

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Abstract: The outbreak of corona virus disease in December 2019 in China spread rapidly across all parts of the world by January 2020. The World Health Organization (WHO) termed it as COVID-19 and declared it a pandemic on January 30, 2020. Till June 8th, 2020, the number of confirmed cases is around 7 million globally, and the global fatality rate is around 3-4%. Since it is a highly contagious disease and is spreading rapidly, governments of almost all of the affected countries are taking it on priority to isolate infected individuals as early as possible. The general symptoms of COVID-19 patients are flu-like such as fever, cough, dyspnea, breathing problem, and viral pneumonia. But these symptoms alone are not significant. There are many cases where individuals are asymptomatic but their chest CT scan and the pathogenic test were COVID-19 positive. So, along with symptoms, positive pathogenic testing and positive CT images/X-Rays of the chest are being used to diagnose the disease. Deep Learning (DL) techniques specifically Convolutional Neural Networks (CNN) has proven successful in medical imaging classification. Four different deep CNN architectures were investigated on images of chest X-Rays for diagnosis of COVID-19. These models have been pre-trained on the train-test database thereby reducing the need for large training sets as they have pre-trained weights. It was observed that CNN based architectures have the potential for diagnosis of COVID-19 disease.

Keywords: Convolutional Neural Networks (CNN), COVID-19 positive, X-Rays for diagnosis of COVID-19, Deep Learning (DL), pneumonia or no pneumonia, Artificial Intelligence, RGB2GRAY, image pre-processing and resizing.

I. INTRODUCTION

With the rapidly surging pandemic, the demand for efficient COVID-19 detection has dramatically increased. The lack of availability of COVID-19 viral and antibody test-kits, and the time required to obtain the test results (in the order of days to weeks) in many countries are posing a great challenge in developing/rural areas with less equipped hospitals or clinics. For instance, in many developing countries, hospitals do not have sufficient COVID-19 test-kits, and therefore, they require the assistance of more advanced medical centers to collect, transport, and test the samples. This creates a bottleneck in mass testing for COVID-19. Therefore, to meet the daily demand for an enormous amount of new test cases, an automated and reliable complementary COVID-19 detection modality is necessary, particularly to confront the second wave of the pandemic. Radiograph image utilization for initial COVID-19 screening may play a pivotal role in areas with inadequate access to a viral/antibody testing. In several studies, CT scans were used for analysing and detecting features of COVID-19 due to higher resolution of features of ground glass opacities and lung consolidation compared to chest X-ray images. However, due to infection control matters associated with patient transport to CT suites, relatively high cost (for procurement, operation and maintenance of CT equipment), and the limited number of CT machines in developing/rural areas, CT scan is not a practical solution for detecting COVID-19. On the other hand, chest X-ray can be employed to identify COVID-19 or other pneumonia cases as a more practical and cost-effective solution because X-ray imaging equipment are pervasive at hospital ERs, public healthcare facilities, and even rural clinics. Even for trained radiologists, detecting chest X-ray images pose challenges to distinguish between features of COVID-19 and community acquired bacterial pneumonia. Moreover, the influx of patients into hospital ERs during pandemic, manual inspection of radiograph data and accurate decision making can lead to a formidable tradeoff between detection time and accuracy that can overwhelm the radiologist department. Therefore, an automated classification technique needs to be designed. As the second wave of COVID-19 is expected in many countries, preparedness to combat the pandemic will involve increasing use of portable chest X-ray devices due to widespread availability and reduced infection control issues that currently limit CT utilization. In the following section, we address the aforementioned problem and present a deep learning-based approach to effectively solve the problem. [1] [2]

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II.PROBLEM STATEMENT

Deep Learning techniques are artificial neural networks in which each layer has multiple neurons that function similarly to the neurons of the human body. Convolutional neural networks (CNNs) are one of the deep learning techniques that have proven to be successful and effective in the field of medical imaging classification. There have been several studies that have used CNN to diagnose pneumonia and other diseases based on radiography. CNN based architecture has been proposed in to identify different lung diseases. In, the Chest X-Ray dataset consisting of around 1,000 X-ray images was used to train a CNN model for the diagnosis of covid-19 disease. CNN has also been used for predicting pneumonia. A recommendation system has been proposed in that helps radiologists to identify infected areas in CT images. [3] [4]

III.METHODOLOGY

A. Data Acquisition

A total of 1000 Chest X-Ray images were collected from public databases available on various GitHub repositories. Among these, 400 were of COVID-19 positive patients and 600 were of patients who did not have the virus. Images were classified as COVID-19 and Non-COVID-19. Some samples of images belonging to the classes COVID19 and Non-COVID-19 have been shown in figure 1 and figure 2 respectively.

B. Data Splitting

The ratio used to divide the dataset into training and testing sets was kept at 75:25. For training 750 records were used and 250 were used for testing. The validation set is kept as 30% of the training set.

C. Data Preprocessing

The image which is in jpg or jpeg format is fed to the pre-processing unit where RGB to Gray conversion takes place and the image is resized at 1:1 ratio (100/100) as shown in figure 3.

D. CNN algorithm

Next, we need to train a deep learning model which can take advantage of the robust dataset obtained from our proposed algorithm. Since the problem can be regarded as a classification task of normal, COVID-19, and other abnormal cases (e.g., pneumonia), we investigate the contemporary deep learning architectures suited for classification. In contrast with other variants of deep learning architectures (i.e., long-short term memory (LSTM), deep belief networks, and so forth) and extreme learning machines, CNNs are regarded as the most powerful deep learning architecture for image classification. Therefore, we explore the robust CNN models recently employed to gain reasonable classification accuracy with chest X-ray data. By applying the contemporary CNN models on the latest dataset compiled from four public repositories, we realize that their reported performances are constrained by overfitting and influenced by biased test data. To address this issue, we propose a two-dimensional (2-D), custom CNN model for classifying X-ray images to predict COVID-19 cases as depicted in Fig. 3. The 2-D CNN structure is utilized to learn the discriminating patterns automatically from the radiograph images. The proposed CNN model consists of three components. The first component is a stack of n_c convolution layers while the second segment consists of n_d fully connected layers. The final component is responsible for generating the output probability. At first, the convolution layers (i.e., the first component of the model) receive radiograph images (X) as input, identify discriminative features from the input examples, and pass them to the next component for the classification task. Each i^{th} layer among the n_c convolution layers consists of a filter size of z^i. Initially, the filter size is set to x_{ir} in the 1st layer, and it is decreased by λ in each successive layer. Figure 4 shows the CNN algorithm architecture. [5]

E. Iterations

Online Jupyter Notebook based service Collaboration by Google Research was used to execute the Python code. The Tesla P4 GPU was used for faster processing which is provided by Collaboratory. Adadelta Optimizer was used to train all the networks and Mean Squared Error was used as the loss function. For training, the batch size was set to 32 and the number of epochs was set to 25. Figure 5 shows the implementation of the same. [6]

F. Real-time Testing

Real- time images are fed to the system and now the trained system takes decisions based on the matrix formation and CNN model. Figure 6 shows the block diagram of this implementation. Finally the image is classified as PNEUMONIA or NON-PNEUMONIA. [7]

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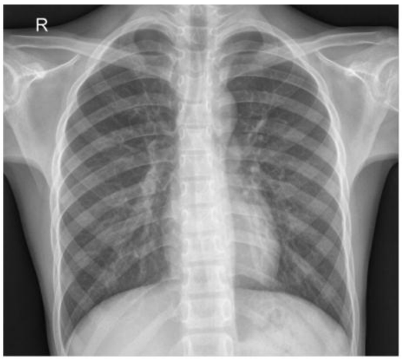

Figure 1 shows chest X-ray of a healthy person

Figure 2 shows chest X-ray of an unhealthy person

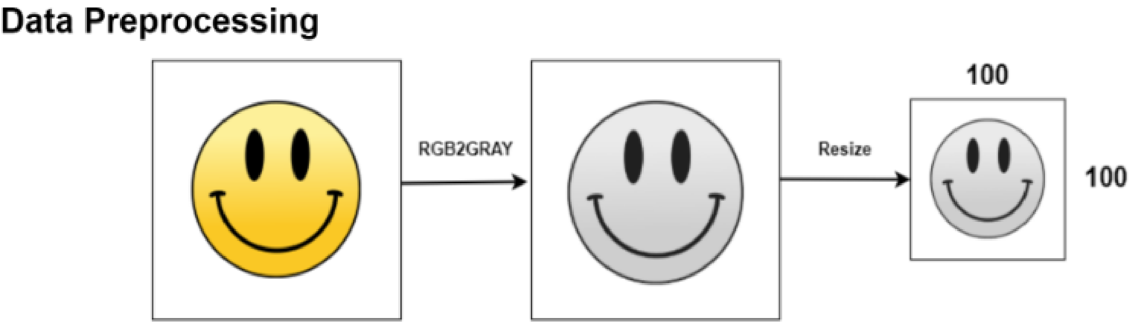

Figure 3 shows the process of pre-processing

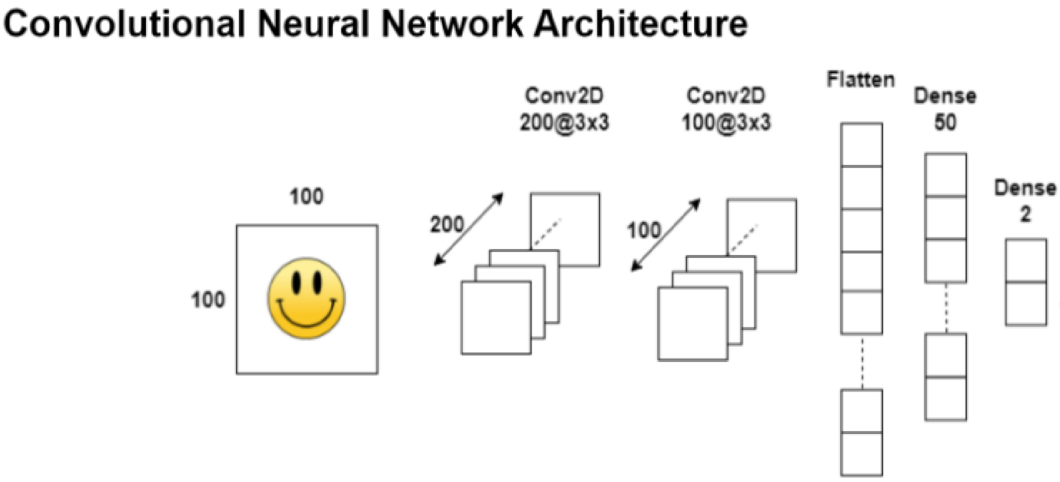

Figure 4 shows the CNN architecture.

IV. CONCLUSIONS

COVID-19 is affecting the health of the global population at an alarming rate. Testing of large numbers of individuals is crucial to curb the spread of disease. Real- time PCR is a gold standard pathological test for the diagnosis of this disease. But the increasing number of negative false reporting has led to the use of Chest X-rays as an alternative for diagnosis of COVID-19. Deep Learning based recommender systems can be of great help in this scenario when the volume of patients is very high and required radiological expertise is low. In this study, four different deep CNN architectures were investigated on images of chest X-Rays for diagnosis recommendation of COVID-19 patients. These models, pre-trained on COVID 19 database, have pre-trained weights that help to transfer their prior knowledge on the dataset being investigated. [8] [9]

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```
In [15]:  from sklearn.model_selection import train_test_split

          train_data,test_data,train_target,test_target=train_test_split(data,target,test_size=0.1)

In [16]:  checkpoint = ModelCheckpoint('model-{epoch:03d}.model',monitor='val_loss',verbose=0,save_best_only=True,mode='auto')
          history=model.fit(train_data,train_target,epochs=15,callbacks=[checkpoint],validation_split=0.25)

          Train on 991 samples, validate on 331 samples
          Epoch 1/15
          991/991 [==============================] - 48s 49ms/step - loss: 0.5688 - accuracy: 0.6811 - val_loss: 0.4414 - val_accurac
          y: 0.8006
          Epoch 2/15
          991/991 [==============================] - 51s 51ms/step - loss: 0.2726 - accuracy: 0.9001 - val_loss: 0.2113 - val_accurac
          y: 0.9215
          Epoch 3/15
          991/991 [==============================] - 51s 51ms/step - loss: 0.1558 - accuracy: 0.9425 - val_loss: 0.1685 - val_accurac
          y: 0.9486
          Epoch 4/15
          991/991 [==============================] - 50s 50ms/step - loss: 0.1153 - accuracy: 0.9586 - val_loss: 0.1296 - val_accurac
          y: 0.9607
          Epoch 5/15
          991/991 [==============================] - 50s 50ms/step - loss: 0.1212 - accuracy: 0.9506 - val_loss: 0.1287 - val_accurac
          y: 0.9607
          Epoch 6/15
          991/991 [==============================] - 50s 51ms/step - loss: 0.0890 - accuracy: 0.9667 - val_loss: 0.1248 - val_accurac
          y: 0.9486
          Epoch 7/15
          991/991 [==============================] - 50s 51ms/step - loss: 0.0515 - accuracy: 0.9839 - val_loss: 0.1284 - val_accurac
          y: 0.9577
          Epoch 8/15
          991/991 [==============================] - 53s 54ms/step - loss: 0.0772 - accuracy: 0.9748 - val_loss: 0.1372 - val_accurac
          y: 0.9547
          Epoch 9/15
          991/991 [==============================] - 50s 51ms/step - loss: 0.0766 - accuracy: 0.9778 - val_loss: 0.1585 - val_accurac
          y: 0.9517
          Epoch 10/15
          991/991 [=========                                                - val_loss: 0.1245 - val_accurac
```

Figure 5 shows the implementation of CNN with epochs= 15/25

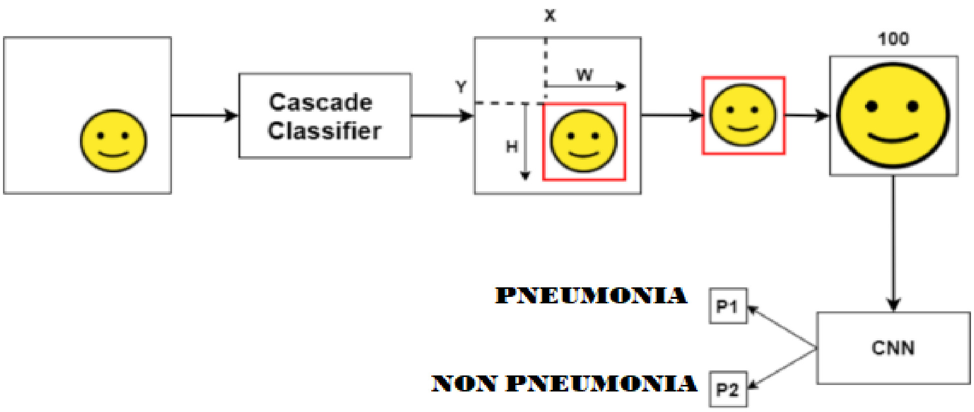

Figure 6 shows real time testing with test samples

```
In [18]:  plt.plot(history.history['accuracy'],'r',label='training accuracy')
          plt.plot(history.history['val_accuracy'],label='validation accuracy')
          plt.xlabel('# epochs')
          plt.ylabel('loss')
          plt.legend()
          plt.show()
```

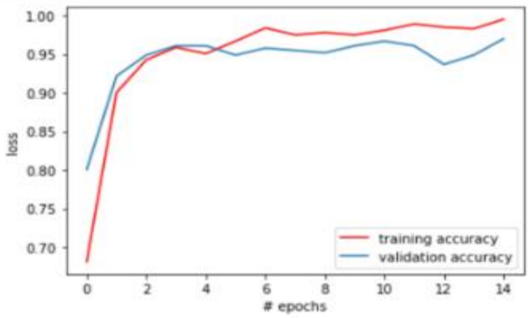

Figure 7 shows the graph of number of epochs vs. Loss.

V. FUTURE ENHANCEMENTS

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The results suggest that CNN based architectures have the potential for the correct diagnosis of COVID-19 disease. Transfer learning plays a major role in improving the accuracy of detection. Fine-tuning of these models may further improve the accuracy. Other pre-trained models may also be explored for building a recommender diagnosis system. Future work may include developing new architectures based on CNN for the detection of COVID-19 as well as other diseases in the medical domain. Also, validation loss can be reduced and thereby increasing the detection accuracy by the AI unit. Figure 7 shows the graph of number of epochs vs. Loss. [10]

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