INTELLIGENT COVID-19 DETECTION FROM CHEST X-RAYS

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ABSTRACT - *It has been more than a year since the first COVID-19 was identified in Wuhan, China. Still, we have not found a faster method which is at the same precision for the detection of COVID-19 disease. There is an urge for new methods because the disease is spreading at a faster pace and it is significant to save the lives of the infected as soon as possible in case of infection. For this reason, we can seek the help of Deep Learning techniques besides the traditional methods for accurate detection of the coronavirus disease at a faster pace. Also, by using these techniques, we can reduce human errors and other medical expenses that occur during the detection of the virus. In this literature, we have used the architecture of Convolution Neural Network (CNN) to detect the virus and spread awareness about it. This paper is an encapsulation of detecting the virus and a place where we can get the overall information about the virus obtained from legitimate sources.*

KEYWORDS: Deep Learning, Chest radiography, COVID-19, Coronavirus, Convolution Neural Networks, Medical Imaging.

1. INTRODUCTION

This project is about to build a web application wherein the users can upload their X-Ray as an image file and the result is displayed to the user. The output is the classification labels, COVID, Viral Pneumonia or Normal which depends on the X-Ray image uploaded. Also, some information regarding the COVID-19, do's and don'ts and many such awareness is also displayed to the user. Along with this, the last two day's recovered, deceased and new cases are also displayed for the user. These information are obtained from legitimate sources. Users can find all the necessary significant information regarding the virus inside this single web application.

The highly contagious coronavirus is spreading at a faster pace. The respiratory droplet of the infected person is the medium of spread. The person infected with the virus will suffer from respiratory illness and if the infection is acute, it may lead to death. This creates a need to detect the positive cases accurately as soon as possible in order to reduce the mortality rate.

The current methods which are utilized to detect the virus are: Reverse Transcription Polymerase Chain Reaction (RT-PCR) where the Ribonucleic acid (RNA) is tested for the presence of the virus using a cotton swab, Saliva test where the saliva of a person is taken in a test tube or the sample is collected using a cotton swab and the RNA of the virus is converted to its DNA and then the DNA is amplified for further processes, Antigen Test which is similar to the RT-PCR but it is more likely to miss active infection, Antibody Test which is conducted on blood samples test for proteins or antibodies that our immune system secretes in order to fight off the virus. These are the most commonly used techniques and there are other methods as well. These methods have many severe limitations that put the lives of many people at risk. One such limitation is these methods are not accurate all the time as they produce many false negatives thereby putting lives of the infected at risk. These methods are very slow in detecting the virus and as the virus spread at a faster pace, there is a need for other faster methods for detection. Also, in the above methods, medical specialists are required to conduct the testing thereby putting their lives at a greater risk because they are in close contact with the infected person.

These limitations could be overcome by chest radiograph (CXR) images and Computer Tomography (CT) scans as a substitute and by using deep learning methodologies like Convolution Neural Network models to detect the virus in those images. This technique takes a few minutes to issue the result and at the same time it is very accurate thereby, reducing errors caused by humans to a greater extent. These images can be used not only to diagnose COVID-19 virus but also other lung diseases like viral or bacterial Pneumonia that might cause similar imaging as that of COVID. Use of technology in the medical field has improved the accuracy and also it reduces the risk taken by medical practitioners to a greater extent.

For this paper, CXR images are collected from various resources to classify the uploaded images as COVID, normal and pneumonia. For the training and testing of dataset, a Convolution Neural Network model is proposed. This deep learning model accurately classifies the images into one of the three categories as mentioned above.

The following is the paper's orientation. Section two contains relevant works. Section three contains the dataset description. Section four tells about the proposed approach which includes: data preprocessing and augmentation techniques, data splitting, proposed model, performance metrics and the tools used. Section five contains the experimental results. Section six describes the prototype tools. Section seven concludes the paper.

2. RELATED WORKS

In [2] the authors made use of the transfer learning model for the COVID-19 diagnosis. This model included two pretrained models: ResNet-34 and ResNet-50 which were primarily trained on the ImageNet dataset that consisted of 3.2 million images for the classification purposes. An accuracy of 66.67% on ResNet-34 and an accuracy of 72.38% on ResNet-50 was obtained.

Further, in [3] the authors compared three different deep learning models such as: Inception net V3, Xception net and ResNeXt for the COVID-19 diagnosis. For this purpose, 6432 COVID-19 images and Pneumonia CXR images were used. A 97 percent accuracy rate was achieved using the Xception net model and it is considered to be the best model among the other two models.

In [4] the authors used Ensemble Learning models that were based on a weighted average that contained three pre-trained CNN models which includes: DenseNet201, ResNet50V2 and Inception V3. Adam optimizer was used for faster convergence in all the three models. An accuracy of 95.7% and a sensitivity of 98% was obtained.

Further, in [5], the authors compared the performance of ConvNet models using Experimentation Learning methodology. The experiments conducted include: Transfer Learning experiments, ConvNet, and Statistical measurement. These experiments were sub categorized as: Covid-19/normal/pneumonia, Covid-19/normal and Covid-19/pneumonia. 94.10% efficiency was obtained using one of the ConvNet architectures.

In [6], the authors proposed a transfer learning model, a fully automated diagnosis method to detect Covid-19 infection. Four pre-trained models were utilized which include VGG16, DenseNet121 [25], ResNet50 [26] and VGG19 [27]. The models were pre-trained using the ImageNet dataset, and then they were further trained using the X-Ray dataset. The number of epochs for each model was set to 30, and the neutron feature extraction range was expanded using the ReLU activation function. VGG19 achieved 100% sensitivity and 99.33% accuracy.

Further, in [7], the authors trained and validated 29 AI-based models using Transfer Learning approach. A number of hyperparameters including Number of epochs, Filter size, Number of filters, fully connected layers, Number of Iterations, Image size, internal validation size and Batch Size. The datasets were augmented using augmentation techniques due to the need for a large amount of data and the restricted availability of COVID-19 CXR images. The model that made use of 101 epochs achieved 93.8% accuracy.

3. DATASET

Since it has been only a year since the outbreak of corona, only a limited number of CXR images are available. We gathered CXR data from a variety of sources and compiled it into a single dataset. Table 1 lists the data sources.

4. PROPOSED APPROACH

4.1. DATA PRE-PROCESSING AND AUGMENTATION

Data augmentation is a strategy for increasing the variance of our dataset by using random transformation. Having a huge dataset is vital to achieve effectiveness in the performance of the deep learning model. So we performed various data augmentation techniques like rescaling, zooming, height and width shifting and flipping since the size of our dataset is very small and also to avoid the problem of model overfitting. The rescaling function reduces or magnifies the image during the augmentation process.

Table 1: Data sources

DATABASES	URL
Kaggle	https://www.kaggle.com/
IEEE Xplore	https://ieeexplore.ieee.org/
Research Gate	https://www.researchgate.net/
Springer Link	https://link.springer.com/
MDPI	https://www.mdpi.com/
Hindawi	https://www.hindawi.com/
SAGE journals	https://journals.sagepub.com/

The angle of the image is clipped in an anticlockwise direction with a shear width of 0.2 percent. The zoom range zooms the picture in and out at a rate of 0.2 percent at random. Then the height of the image is shifted with the factor of 0.2 and width of the image is also shifted with the factor of 0.2. Furthermore the images are randomly rotated to 40 degrees. Finally the images are flipped horizontally. After this, the augmented images are resized to the size of 224 X 224.

4.2. DATA SPLITTING

A total of 8252 images are divided into training and testing dataset of 8115 and 137 images respectively. Then both the training and testing dataset are segregated into three sets namely normal, covid and viral pneumonia images. In the training dataset, there are 2692 normal chest radiograph images, 1118 corona virus disease affected chest radiograph images and 4305 viral pneumonia chest radiograph images. There are 30 corona virus disease affected chest radiograph images, 65 viral pneumonia chest radiograph images and 42 normal chest radiograph images in the testing dataset. Thus the dataset is set up to train the model which is followed by testing the efficiency of the trained model.

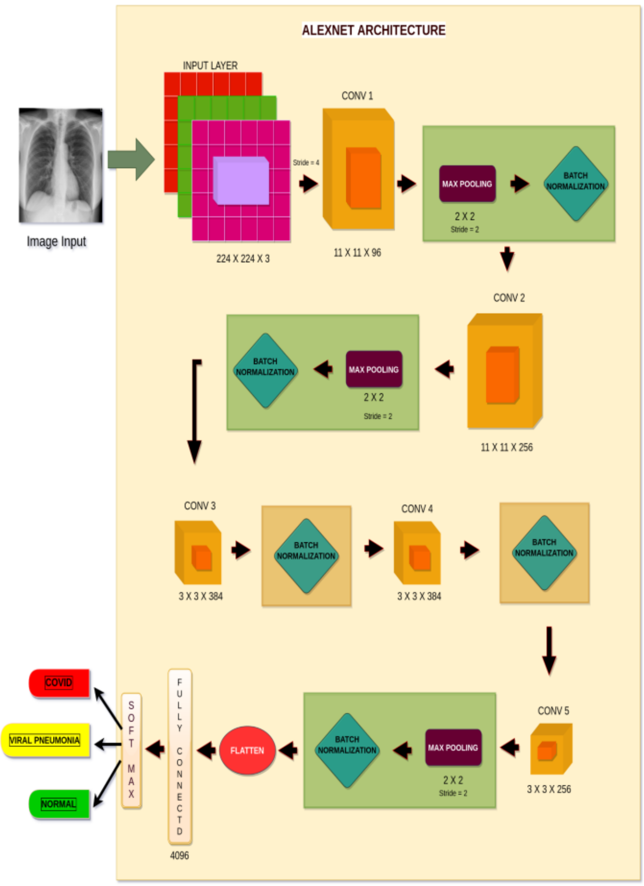
4.3. PROPOSED MODEL

One of the most renowned architects in deep learning is the Convolution Neural Network (CNN). It is now a go-to model for every image analysis and image classification problem. AlexNet is a convolution neural network which had a large impact on the application of deep learning to computer vision. Convolution layers and fully connected layers make up a standard AlexNet architecture. Inspired by the AlexNet architecture, combining one or more such layers, we have designed an automated Covid-19 detector that detects Covid-19 from CXR images.

The proposed architecture is made up of Convolution, max-pooling, normalization, and fully connected, with the Relu activation feature added after each convolution and fully connected layer. Each level accepts the output of the level immediately preceding it as input. The image size is fixed to 224 X 224 X 3. There are five convolution layers that is conv2D layers with each layer having 96 kernels of size 11 X 11, 256 kernels of size 11 X 11, 384 kernels of size 3 X 3, 384 kernels of size 3 X 3 and 256 kernels of size 3 X 3 respectively. A stride of 4, 1 and 2 is applied to convolution layers. The convolved images are subjected to batch normalization. It is followed by the rectified linear unit (ReLU). The input is standardized by Batch normalization. ReLU activation function is used to avoid model overfitting. Three max pooling layers are then applied to sample the height and width of tensors, keeping the depth the same. We used max pooling windows with dimensions of 2 X 2 and strides of 2 between adjacent windows. Dropout increases the number of iterations required to converge in a fully connected layer by a factor of 0.2 and 0.4 respectively. Finally this ends with a SoftMax layer that produces the output. Weights are generated using SGD optimizer with 0.001 initial learning rate and 0.9 momentum. The model performs the task of classification into three different labels namely covid, viral pneumonia and normal.

The specifics and parameters of the layers are shown in table 2.

Figure 1. AlexNet Architecture



4.4. PERFORMANCE METRICS

We employed the metrics, classification accuracy and error rate to compute the performance of our proposed model. These metrics are computed in terms of correct/incorrect classification of x-ray images for each category. Finally, the average of results are taken for the final value. Classification accuracy represents the ratio of correctly classified images (True positives and True negatives) out of the total number of x-ray images. Classification accuracy is estimated as follows:

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

Where classification accuracy, true positive, true negative, false positive and false negative are all abbreviated as A, TP, TN, FP, and FN respectively. Error rate represents the ratio of misclassified images (False positives and false negatives) to the total number of CXR images. Error rate is computed as follows:

Table 2. The specifics and the parameters of the layers of the proposed model

Order of Layer	Type of Layer	Output Shape	Parameters
1	Conv2D	[54, 54, 96]	34944
2	Max Pooling	[27, 27, 96]	0
3	Batch Normalization	[27, 27, 96]	384
4	Conv2D	[17,17,256]	2973952
5	Max Pooling	[8, 8, 256]	0
6	Batch Normalization	[8, 8, 256]	1024
7	Conv2D	[6, 6, 384]	885120
8	Batch Normalization	[6, 6, 384]	1536
9	Conv2D	[4, 4, 384]	1327488
10	Batch Normalization	[4, 4, 384]	1536
11	Conv2D	[2, 2, 256]	884992
12	Max Pooling	[1, 1, 256]	0
13	Batch Normalization	[1, 1, 256]	1024
14	Flatten	[256]	0
15	Dense	[4096]	1052672
16	Dropout	[4096]	0
17	Batch Normalization	[4096]	16384
18	Dense	[4096]	16781312
19	Dropout	[4096]	0
20	Batch Normalization	[4096]	16384
21	Dense	[1000]	4097000
22	Dropout	[1000]	0
23	Batch Normalization	[1000]	4000
24	Dense	[3]	3003

$$FP + FN$$

E = ----------------------------
TP + TN + FP + FN

Where Error rate, true positive, true negative, false positive, and false negative are all abbreviated as E, TP, TN, FP, and FN respectively.

4.5. TOOLS USED

For the implementation, we used PyCharm Professional (students' version), Python 3.7.9 and TensorFlow 1.15.2. For the implementation of Convolution Neural Networks (CNN), the deep learning library of TensorFlow 1.15.2, Keras 2.2.4 is used. The training and the testing processes are performed using the PyCharm platform.

5. EXPERIMENTAL RESULTS

The models have been trained for 50 epochs. SGD (Stochastic Gradient Descent) is an iterative approach for improving the smoothness properties of an objective function [1]. SGD optimizers have been used for generating weight with an initial learning rate of 0.001 and momentum of 0.9. Then the model is saved as .hdf5 file.

The time taken for training was 693 seconds / epoch. Figure. 2 depicts the gradual change in model's training and validation accuracy. Figure. 3 depicts the gradual change in training and validation loss of the proposed model. The covid class has much less data points than the other two (pneumonia and normal) classes, resulting in a sharp increase and decrease in the graphs.

As the deep learning model analyses all the images repeatedly for every epoch when training, however, the rapid increase and decrease is gradually decreased in the later stages.

The proposed classification model achieved an overall training accuracy of 83 % and the validation accuracy of 80.14 %. We repeated the training phase several times to affirm the performance of our proposed model, yielding the same results each time. The study's scope was restricted by the amount of data available. Significant improvements can be made with better data access.

Figure 2. Training and validation accuracy

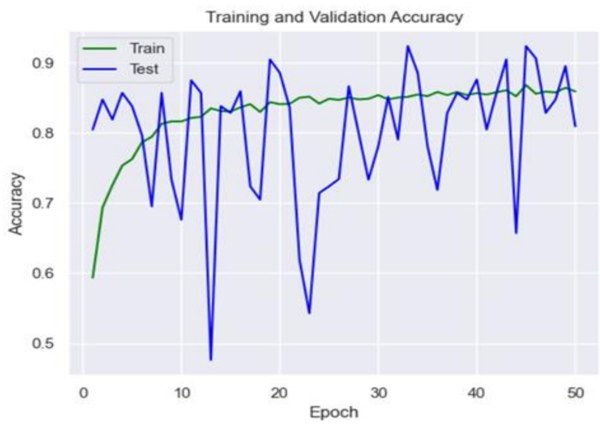
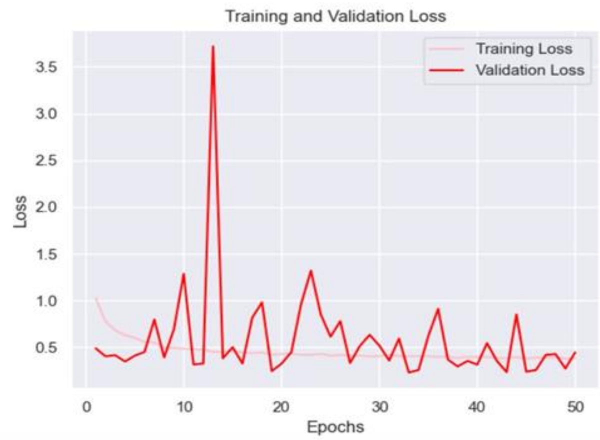


Figure 3. Training and validation loss



6. PROTOTYPE TOOL

Based on the solution proposed, a simple web application has been developed. This can be utilized to detect corona virus disease positive cases and to distinguish coronavirus disease affected patients from viral pneumonia infected patients and the normal people. This allows people to browse a chest x-ray image and feed it to the application. The web application in turn will analyze the image and based on the results of the model proposed in this work, it will provide a label for the uploaded chest x-ray image. Depending on the analysis result, the label displayed can be either covid-19 or viral pneumonia or normal. This portal can be used for the fast detection of coronavirus disease.

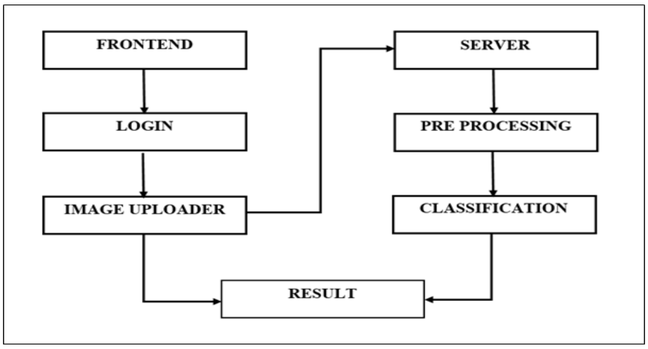
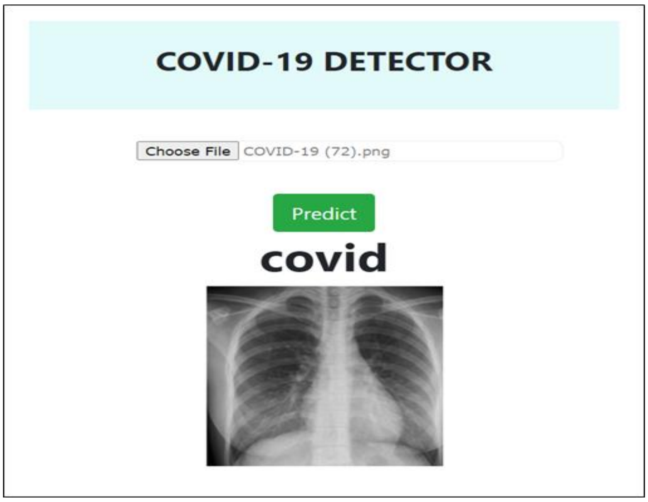


Figure 5. Web application for Covid-19 detection



7. CONCLUSION

Thus, using the Convolution Neural Network architecture, we are able to successfully classify the given CXR image file into normal, covid and viral pneumonia. The project is built from scratch using the AlexNet Convolutional Neural Network to train the Chest X-Ray images. Along with classifying the images, the information available on our website will be really helpful to get an overall insight about the spread of the virus and also the necessary safety measures suggested by renowned medical practitioners. This project can also be extended in the future to detect other lung related diseases without much human intervention. Also, the average accuracy can be increased by using more CXR images in both the training and testing phases. With this automation of detecting the presence of Covid, we hope that health care delivery will be improved, saving time as well as the lives of the infected and also the medical practitioners.

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