2020 23rd International Conference on Computer and Information Technology (ICCIT), 19-21 December, 2020

Detection of COVID 19 from CT Image by The Novel LeNet-5 CNN Architecture

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2020 23rd International Conference on Computer and Information Technology (ICCIT) | 978-1-6654-2244-4/20/$31.00 ©2020 IEEE | DOI: 10.1109/ICCIT51783.2020.9392723

***Abstract*—The COVID-19 is an infectious disease that primarily affects the lungs and leads to death in the severe stage. It also changes the lung CT scans of affected patients. For introducing a more convenient COVID-19 identification technique during this pandemic, we have implemented a simple convolution neural network (CNN) based model by using lung CT images. And finally, we have used LeNet-5 CNN architecture for this purpose. For training and testing purposes, we have obtained a dataset that contained 349 COVID-19 lung CT frames and 397 number of NON COVID-19 CT frames. We have introduced the data augmentation technique and got 1744 CT frames of COVID-19 and 1588 CT frames of NON COVID-19 patients. Among them, we have used 80% of lung CT frames for training purposes and 20% frames for testing purposes. The total number of trainable parameters of our LeNet-5 CNN architecture was 82,146. After completing the whole process, we got the accuracy of 86.06%, f1 score of 87%, the precision of 85%, and recall of 89%, and area under the ROC curve of 0.86 for COVID-19 detection.**

***Index Terms*—COVID-19 Lung CT Scan, LeNet-5, CNN, Classification Problem, Performance Metrics**

I. INTRODUCTION

An eruption of novel coronavirus disease (COVID-19) pneumonia was first found in the last of 2019 in Wuhan, China's Hubei state [1],[2]. COVID-19 is known as a flourished respiratory dysfunction, and the main reason behind this is the existence of SARS-CoV-2 virus in human lung. This COVID-19 has upended human life in a million ways. The World Health Organization (WHO) revealed a worldwide public health catastrophe on 30th January 2020 for this pandemic [3].

The RT-PCR test or sequencing of the respiratory system is known as a microbiological test for diagnosing the presence of SARS-CoV-2 in a human body [4]. These microbiological tests are not convenient in an emergency because it needs a complex mechanical setup, and highly expertise pathologist. It also takes more time in Bangladesh. However, for the early detection of COVID-19 infection, computed tomography (CT) of the lung with deep learning model will be the best way out during this pandemic in Bangladesh.

CT finding for COVID-19 relates to the radiological examination, such as a slender slice of lung CT is used to detect lung infection by the concept of ground-glass opacity (GGO) [5]. The leading lung CT finding is the multifocal bilateral GGOs with a subpleural distribution and also preferred lower lobe weakness figure (1) [5]. Here in our study, we may differentiate the GGOs features of COVID-19 affected patient and normal subjects by using the deep learning approach on lung CT scans.

As the difference between the sound subjects and affected subjects is the existence of glass-ground opacity of lung CT images, we can identify this by training a LeNet-5 CNN model on lung CT images. For our system design, we have used 80%, 20% of CT lung images from our augmented dataset for training, and testing purposes, respectively. And our trained model has presented much satisfactory results, and those results refer as the performance metrics of a CNN model.

II. RELATED WORK

Researchers have assessed some prediction models for diagnosis purposes of COVID-19 on lung CT [6-10].

- Fang et al. [6] proposed a system for predicting COVID-19 by differentiating the sensitivity of RT-PCR and lung CT. They identified that lung CT is more sensitive for COVID-19 finding.
- Horry et al. [7] imposed a deep learning-based COVID-19 detection system through transfer learning on multiple types of medical image (x-ray, CT, ultra sound).
- Loey et al. [8] introduced a artificial intelligent methodology by a deep transfer learning based concept on CT digital images.
- Xie et al. [9] also revealed that sensitivity calculation of lung CT took a higher position over RT-PCR in the prediction of COVID-19 at an early stage.
- Recently, some deep learning methodologies have been introduced in the diagnosis purposes of pneumonia in chest CT images related to COVID-19 [10].

But now we have the direct lung CT images of COVID-19 affected subjects and not affected subjects, and our aim is to introduce a LeNet-5 CNN architecture based COVID-19 prediction model based on COVID-19 lung CT findings.

III. DATA SOURCE

A. Dataset Collection

As our aim is to introduce a COVID-19 lung CT scan based prediction model, an open-sourced dataset of 349 COVID-19 lung CT frames, and 397 NON COVID 19 lung CT frames

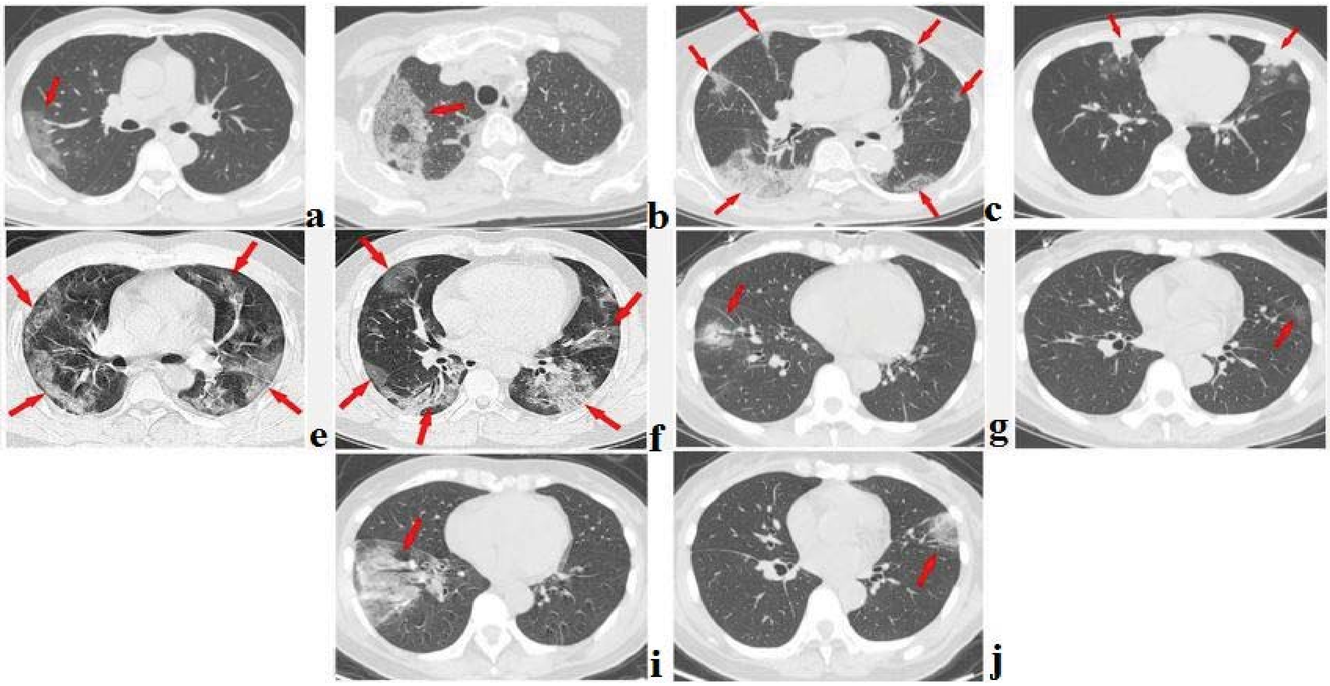

Fig. 1. a, Axial lung CT appeared bitty solid GGO. b, Axial lung CT bitty solid GGO with consistently scattered GGO. c, Axial chest CT showed multiple subpleural distributed GGOs. d, multiple solid consolidation lesions in the middle and upper lobe of right and left lung respectively. e-f, CT images showed diffusely subpleural distributed GGOs . g-h, baseline axial chest CT showed GGO with consolidation in lower lobe of right lung (g) and one pure GGO (h) in the upper lobe of left lung. i-j, axial chest CT showed the disease advancement, appearing as increased extent and consolidation compared with baseline chest CT [5].

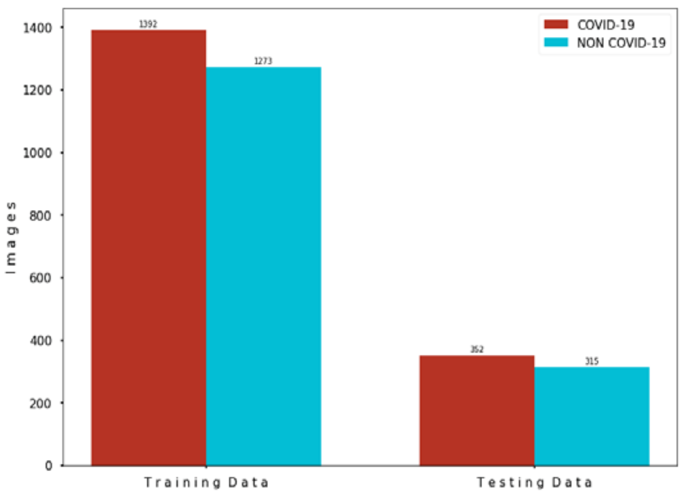

Fig. 2. Augmented image distribution for whole model

were obtained [11]. When we were ready to feed our collected dataset to LeNet-5 model, there we had focused on some preprocessing, for the betterment of system design. But our expected Lenet-5 architecture needed a minimum requirement of preprocessing, and it was so much advantageous for us. With that said, we have imposed minimum preprocessing techniques. And they were, converting RGB CT images to grey-scale, resizing the images, normalization of pixel's values, and data augmentation technique.

B. Data Augmentation

Our obtained dataset is not so big for avoiding over-fitting problems. For this reason, the image augmentation technique was an excellent idea for us. And finally, our collected data set became larger without getting any new images using this technique. And finally 1744 lung CT frames related to COVID-19 and 1588 frames related to NON COVID-19 was obtained by using this augmentation techniques. Class wise frames distribution for training and testing process is given in figure 2. And, 1392 COVID-19 CT frames and 1273 NON COVID-19 CT frames were identified for training, and 352 COVID-19 CT and 315 NON COVID-19 CT frames were also identified for testing. The image augmentation parameters, we have used are given in table 1.

TABLE I
IMAGE AUGMENTATION

Sl.	***Parameters***	***Value***
1	Rotation Range	20
2	Zooming	0.3
3	Width Shifting	0.2
4	Height Shifting	0.2
5	Shearing	0.2

C. Data Preprocessing

CT findings for COVID-19 can be identified easily by using a grey-scale CT image. For that reason, we converted the input

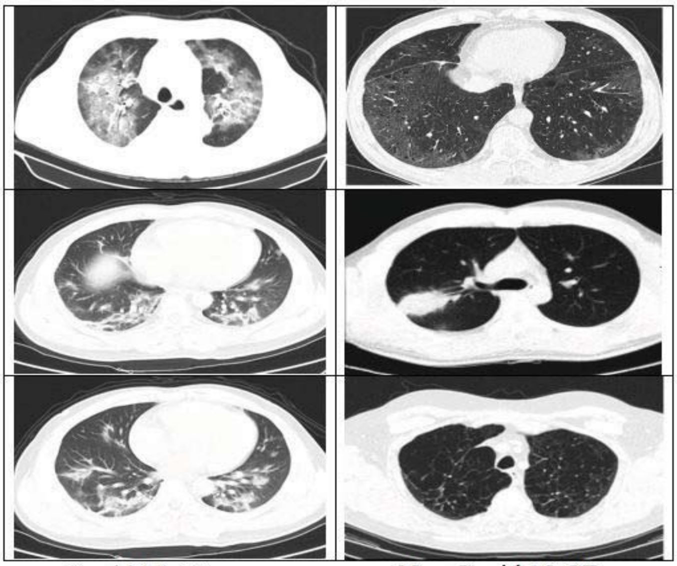

Fig. 3. Lung CT Images of Different Subjects

CT images into grey-scale, and we also re-scaled the pixel values from 0 to 1, and that is known as normalization. As different sizes of input images to the model are perilous, and we have overcome this problem and accelerated our model by setting the input CT image's size to 32x32x1.

IV. LeNet-5 CNN Architecture

There have some numerous deep learning approaches for real-time applications. Among them, Convolutional Neural Network (CNN) became the most popular technique in vision system design and implementation as well as in the medical image processing related classifier model design [13]. LeNet-5 was the first introduced CNN architecture and used for recognizing handwritten characters [12]. And finally, our focus was to predict COVID-19 using the LeNet-5 CNN model from lung CT images.

A. First Layer:

The input for the LeNet-5 CNN model was a 32×32 grey-scale lung CT image that passed through the first convolutional layer, and the number of the filter was 6, and the size was 5×5 with 1 stride value.
Trainable Parameters,
=Weight +Bias
=5×5×1×6+6
=156

B. Second Layer:

Furthermost, the LeNet-5 CNN model was incorporated with an average pooling layer, and the filter size was 2×2 with 2 strides value.

C. Third Layer:

The third layer of LeNet-5 architecture was incorporated with a convolutional layer, and the numbers of the filter were 16 having a size of 5×5 per filter and a stride of one.
Trainable Parameters,
=Weight +Bias
=5×5×6×16+16
=2416

D. Fourth Layer:

The fourth layer was comprised again with an average pooling layer having kernel size 2×2 and two stride value

E. Fifth Layer:

The fifth layer of LeNet-5 architecture was a fully-connected layer with 120 filters, and the size of each kernel was 5×5. Every 120 units in this layer were directly connected to all the nodes in the fourth layer.
Trainable Parameters,
=Weight +Bias
=(576×120)+120
=69240

F. Sixth Layer

The sixth layer of the LeNet-5 model was a fully-connected layer with 84 units.
Trainable Parameters,
=Weight +Bias
=(120×84)+84
=10164

G. Output Layer

Finally, there was a fully-connected sigmoid output layer with two possible values for identifying COVID-19 or Non-COVID 19 subjects.
Trainable Parameters,
=Weight +Bias
=(84×2)+2
=170
Total Parameters = 82,146
Total Trainable Parameters = 82,146
Here, we have used activation function Relu for the betterment, as our work was a binary classification of CT images. The Batch size was 32 and we have trained the model for 157 times. The Summary and the output shape of every layer is given in table (2):

V. Experimental Results

The performance matrix of any CNN architecture refers to the experimental results are based on the test accuracy, test loss, f1 score, and so on [14]. The accuracy and the f1 score cab be expressed by Equation (1) and Equation (4) respectively:

$$accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \tag{1}$$

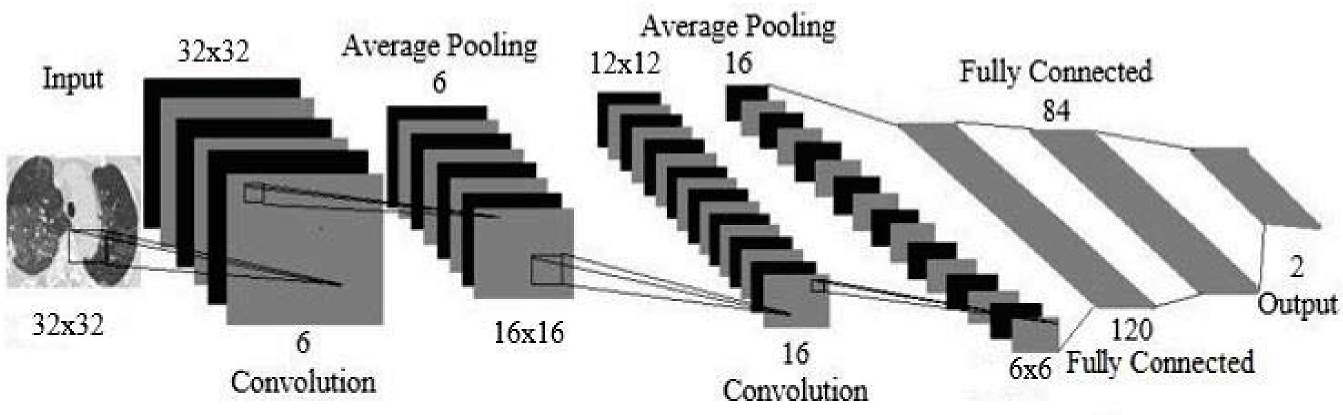

Fig. 4. LeNet-5 CNN architecture

TABLE II
MODEL SUMMARY

	Layer	No. of Filter	Filter Size	Stride	Activation	Output Shape
Input	Image	1	-	-	-	32x32
1	Convolution	6	5x5	1	relu	32x32
2	Average Pooling	6	2x2	2	relu	16x16
3	Convolution	16	5x5	1	relu	12x12
4	Average Pooling	16	2x2	2	relu	6x6
5	Fully Connected	-	-	-	relu	120
6	Fully Connected	-	-	-	relu	84
Output	Fully Connected	-	-	-	Sigmoid	2

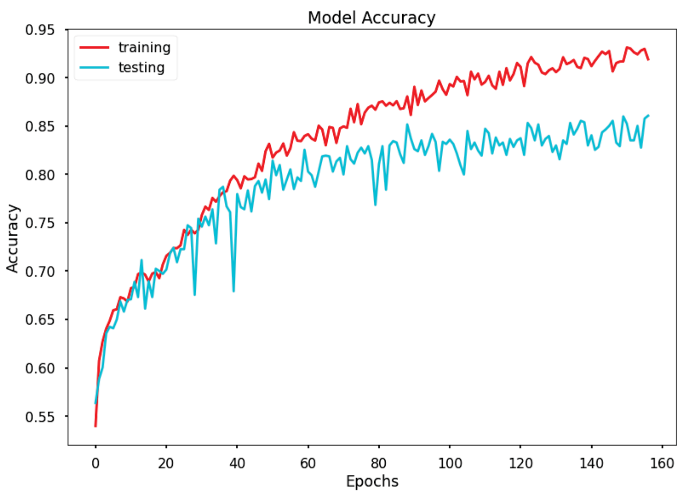

Fig. 5. Accuracy of COVID-19 Detection LeNet-5 Model

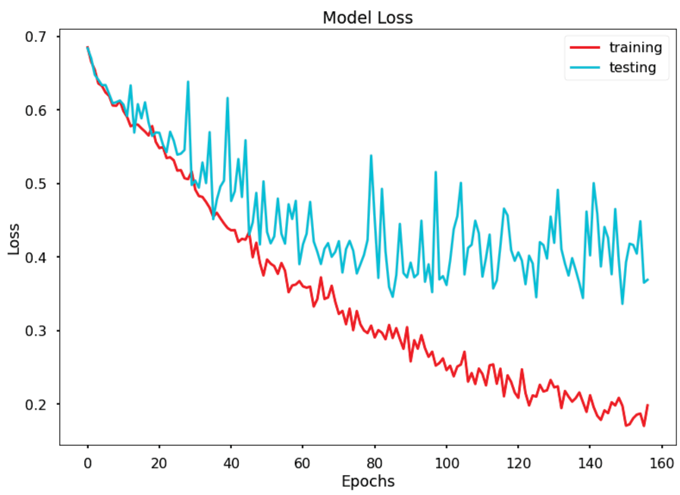

Fig. 6. Loss of COVID-19 Detection LeNet-5 Model

$$P = \frac{Tp}{Tp + Fp} \tag{2}$$

$$R = \frac{Tp}{Tp + Fn} \tag{3}$$

$$f1\ score = 2 * \frac{P * R}{P + R} \tag{4}$$

where, Tp = true positive, Tn = true negative, Fp = false positive, Fn = false negative, P = precision, R = recall

The accuracy (training & testing) curves are presented in figure (5), and the loss (training & testing) curves of our COVID-19 detection LeNet-5 model are also presented in figure (6). Another fundamental curve of the performance metrics is the area under the ROC curve is also presented in figure (7). The confusion matrix is even presented in figure (8). The model have identified 314 COVID-19 CT from 352 COVID-19 CT and 261 NON COVID-19 CT from 315 NON COVID-19 CT.

By using equation (1) and (4), the LeNet-5 COVID-19 detection model reached an accuracy of 86.06%, loss of 0.369 and f1 score of 87%, precision of 85%, recall of 89% after 157 number of iteration for COVID-19 disease identification.

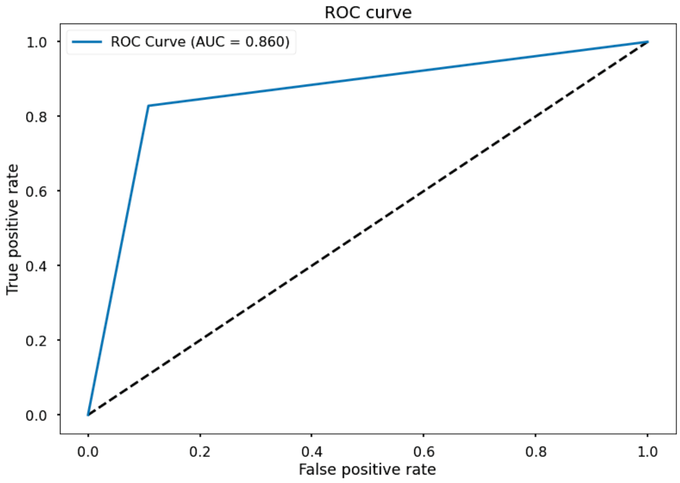

Fig. 7. Area under ROC Curve of our model

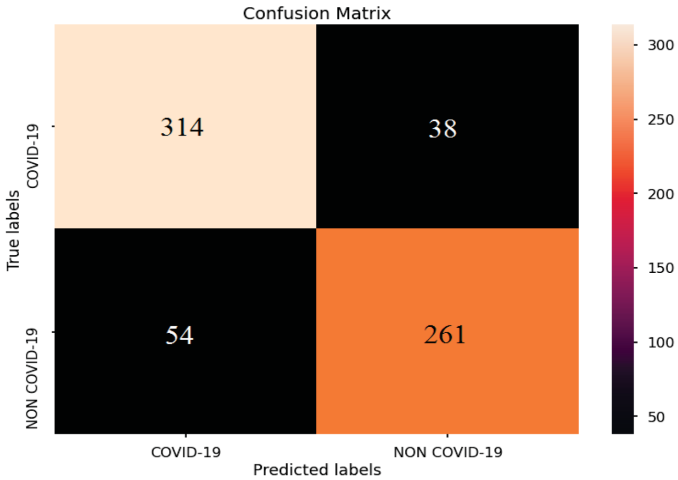

Fig. 8. Final Confusion Matrix

VI. CONCLUSION

This COVID-19 detection model has a great potentiality to make a remarkable impact on the clinical workflow such as in diagnosis purposes of any healthcare system during the pandemic and most importantly in the future. As for the case of the COVID-19 suspect, distancing is the most care about things we got and deep learning approaches are the best solution and we had done it over the lung CT findings of COVID-19 patients and it became reliable source of diagnosis. Some other deep learning model was used [7] for detection of COVID-19 on CT image and reached the highest accuracy of 82.91%. Then other researchers [8] have worked on different medical images through deep learning and have found accuracy of 82%, precision of 79%, and f1 score of 81% and, finally Our proposed model has overcome all those performance parameters. Till now we got the challenge of introducing this type of model in accordance with a larger dataset to solve this pandemic. Our future assessment is to make the model more convenient and efficient enough.

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