COVID-19 DISEASE DIAGNOSIS FROM RADIOLOGY DATA WITH DEEP LEARNING ALGORITHMS

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***Abstract*—Since December 2019, the COVID-19 coronavirus epidemic has spread around the world. In the face of this epidemic, it is important to speed up the diagnosis of the disease in order to reduce the loss of life and to prevent the epidemic from spreading. One of the methods used to diagnose disease is to analyze computed tomography images. In this study, a deep learning algorithm has been developed for disease diagnosis by analysis of computed tomography images. A data set consisting of computerized images of patients with COVID-19, Normal and Pneumonia was used. The results of algorithms with three different network structures are compared.**

***Keywords*— COVID-19 Disease Diagnosis, Deep Learning, VGG-16, ResNet, GoogleNet**

I. INTRODUCTION

COVID-19 is the coronavirus outbreak that occurred in Wuhan, China in December 2019. This disease, which spreads rapidly without choosing gender, race or social class, increases the risk of dying as the age increases [1]. The disease causes serious problems such as acute respiratory disorder and heart problems. Most of the deaths observed are individuals over 60 years of age with chronic conditions such as cardiovascular disease [2].

Early diagnosis and treatment is the most important factor in reducing deaths. In the evaluation of patients, chest radiography and computed tomography are used for screening, diagnosis and treatment of suspected or COVID-19 infected patients [3]. The characteristic findings of COVID-19 on CT scans can make it differentiated from other types of viral pneumonia. However, some symptoms overlap with other viral pneumonia, so it is not reliable based on human observation alone [4]. With the use of artificial intelligence and deep learning technologies, it is possible to accurately differentiate viral pneumonia types and make it an effective screening tool [5].

The aim of this study is to provide the diagnosis of the disease by analyzing the radiography and tomography scans with the deep learning algorithm. It is to provide quick and easy interpretation of the images during the epidemic process that continues all over the world.

II. METHODS AND MATERIALS

A. Convolutional Neural Network (CNN) Architecture

CNNs are one of the most commonly used image classification models of neural networks. Corresponding filters in CNN can capture the spatial and time dependence of an image [6]. CNN reduces the image properties to an easier to edit system without reducing the properties required for good classification. CNN's architecture consists of a layer sequence that uses a different function for each layer to transform one layer into another. There are normally three layers to create a CNN model. These are: convolutional layer, pooling layer and fully connected layer. There are two types of pooling in pooling layers. The first type is maximum pooling that returns the maximum value from the core part of the image, eliminating noisy activation and reducing both noise and size. The second type is average pooling that reduces the size of the matrices and uses this reduction as a noise control mechanism. As a result, maximum pooling is better than average pooling. Generally, CNN uses n rows, m columns, and 3 color channels in an image matrix (R, G and B) and the input 3rd order tensor which takes into account the spatial structural structure of the image. The input passes through the convolution layer, the pool layer and the fully connected layer, where the output of each layer is used as input for the following layer. The network begins with 3 * m * n input neurons that are used to encode pixel densities for input features of a 2-dimensional image. This is followed by a convolution layer in the local receptor domain fxf. The result, when using a 1-period step
$3 \times (m\text{-}f + 1) \times (n\text{-}f + 1)$ it is a layer of latent property neurons. The pooling layer will be applied to 2x2 regions on each of the 3 feature maps and

$3 \times (m\text{-}3 \times (mr + 1) / 2 \times (nr + 1) / 2$ hidden feature neurons will be obtained. The feature map is usually convolution processing by multiplying the Entry matrix element with the filter or core elements, and then the result is collected to obtain a pixel from the feature map.

The filter slides through the input matrix and creates other features. It is written mathematically as shown in equation 5 below [6].

$$O(i,j)=\Sigma(\Sigma input(i+k-1,j+l-1)kernel(k,l)fl=1)fk=1 \quad (1)$$

Here i is from 1 to m-f + 1, j is from 1 to n-f + 1. The activation functions are applied to the data after convolution. The choice of activation function affects the success rate. The most commonly used activation functions are ReLu and Sigmoid functions. The main logic of the ReLu activation function is that it produces zero output value for input negative values and returns the input value exactly for positive values. ReLu is preferred as the activation function. The results were evaluated on the data set defined in this study by using 3 different network models, VGG-16, ResNet, GoogleNet, among the deep learning models. The structure of these CNN network models used is presented in detail below.

1) *VGG16 Transfer Model*

VGG16 is a simple network model and the most important difference from the previous models is that the convolution additions are used in 2 or 3. It is an architecture consisting of 16 convolution layers, 5 pooling layers and 3 fully connected layers. In the convolution layers of this architecture, the convolution process has been carried out with 3x3 cores. Although it has very successful performance values, having many parameters makes it difficult to use. The structure of the VGG16 architecture is shown in Fig.1. Transfer learning was carried out using labeled pantograph images using the VGG16 model.

2) *ResNet Transfer Model*

ResNet [7], which performs the training of very deep networks with its permanent connections, has a deeper, larger and slower structure than GoogleNet. With this model with a depth of 50 layers, higher performance is obtained in the ILSVRC data set compared to GoogleNet. Architecture of the ResNet50 model [7] As shown in Fig. 2. The created data set was trained by giving entries to the last layer using the ResNET50 Transfer Model and tested with test data.

3) *GoogleNet Transfer Model*

GoogleNet network architecture is used as the third model. This architecture is generally one of the first CNN architectures to move away from stacking convolution and pooling layers on top of each other in a sequential structure. It is more complex than other networks. Despite the computational complexity and size, speed and success are higher with the solution found. It consists of modules and each module is called "Inception". Modules are shown in Fig. 3. Each module consists of different size convolution and max-pooling processes. This new model has an important place on memory and power usage. This is because stacking all layers and adding multiple filters costs a calculation and memory, and increases the likelihood of memorization. In order to overcome this situation, GoogleNet modules connected to each other in parallel were used [8].

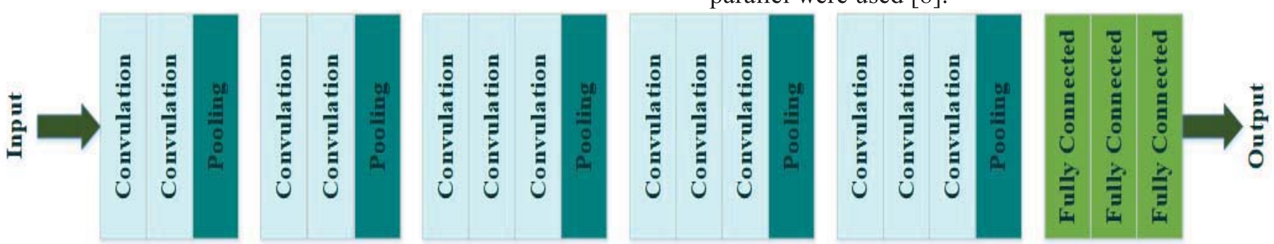

Fig. 1. VGG16 Architecture

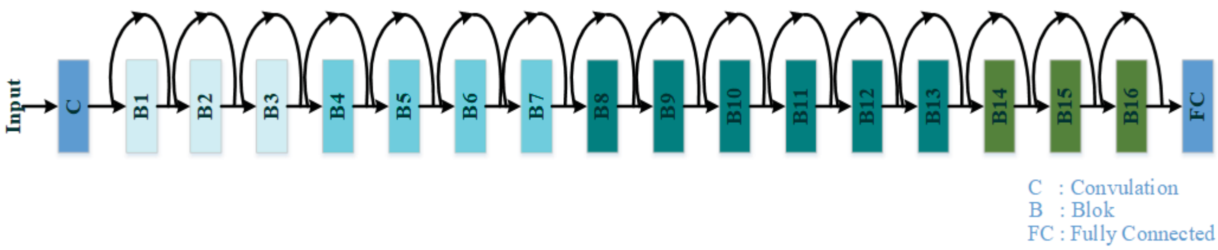

Fig. 2. ResNet Architecture

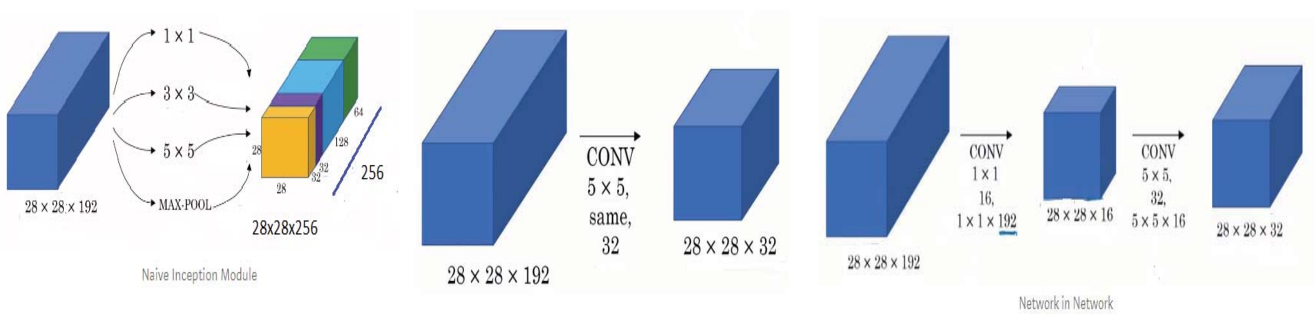

Fig. 3. Inception Module- GoogleNet Architecture

B. Image Acquisition

A research team from the University of Qatar, Doha, Qatar, Bangladesh and Dhaka University, in collaboration with their collaborators in Pakistan and Malaysia, medical doctors, created a database of chest X-ray images and Viral Pneumonia images for COVID-19 positive cases (Fig.5.)

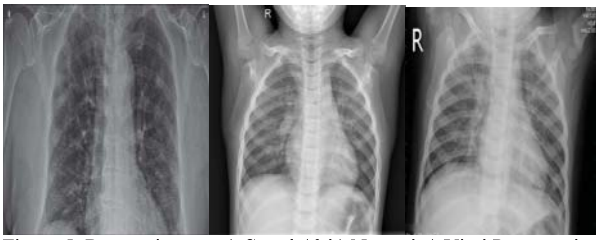

Figure 5. Dataset images a) Covıd-19 b) Normal c) Viral Pneumonia

In the current version of this data set; There were 219 COVID-19 positive, 1341 normal and 1345 viral pneumonia images [9].

Fig. 5. The images shown in the are images belonging to three different classes within the dataset used.

III. Experimental Results

The results were evaluated on the data set defined in this study by using 3 different network models, VGG-16, ResNet, GoogleNet, among the deep learning models. The image classification model is designed to distinguish the appearance and nature of different infections. This study is done in Python language on Anaconda Spyder interface, using Keras library. Learning Rate in each model in the learning algorithm; As "1e-5" and Batch Size; It was chosen as "8". Algorithms are run at 20 epochs. The traning and validation charts of Vgg16, Resnet50 and GoogleNet algorithms are shown in Figure 6, and confusion matrices are in Figure 7. Calculated performance values of the model are presented in Table 1 for "precision", "recall" and "f1 score". The total performance comparison of the networks for the three classes is included in Table 2.

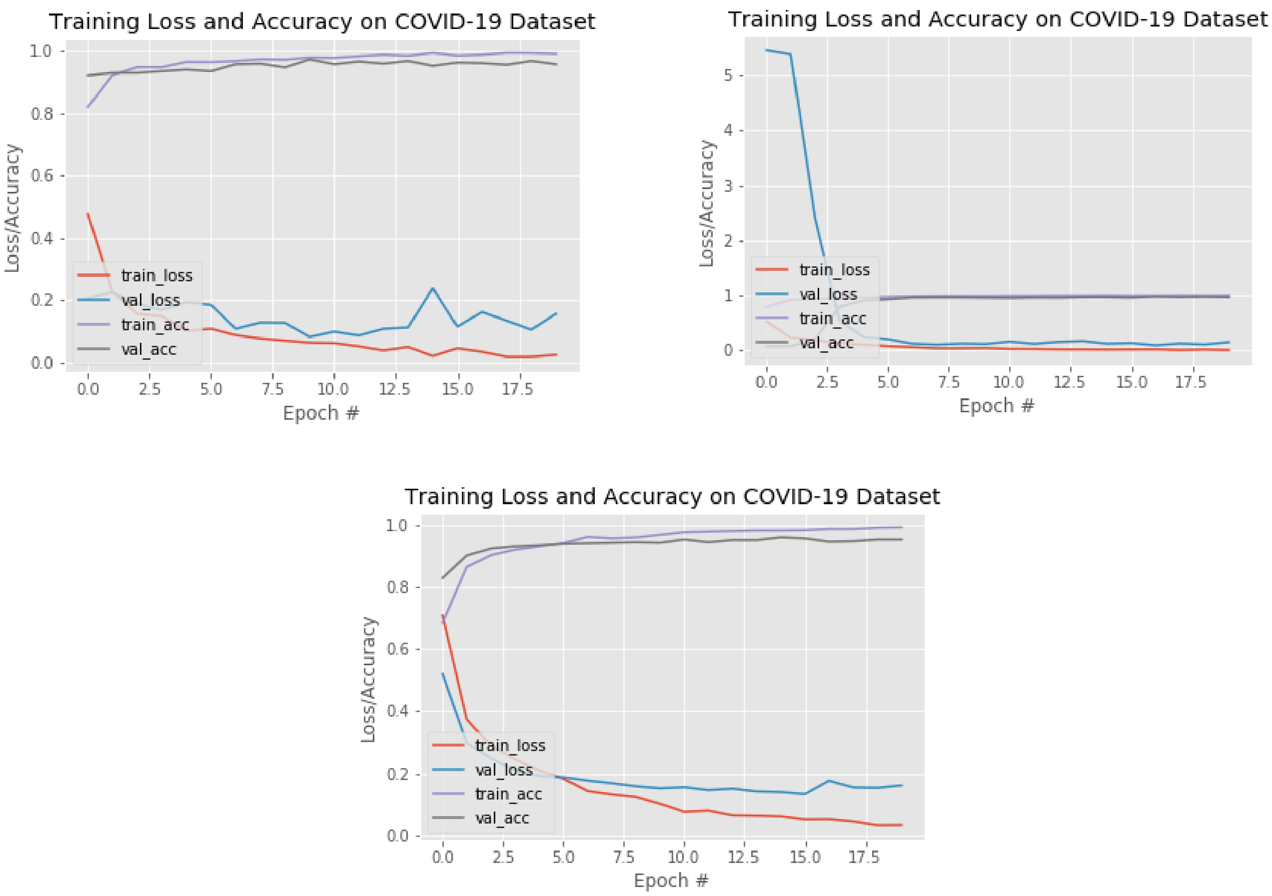

Fig. 6. Evaluation metrics of COVID-19 detection system based on a) VGG16 Model b) Rsnet50 c) GoogleNet

43	1	0
0	264	4
2	17	250

42	2	0
0	268	0
2	16	253

38	1	5
0	257	11
0	11	258

Fig. 7. Confusion matrix for a) Vgg16Net b) Resnet50 c) GoogleNet

Table 1. Precision, Recall and F1 score of CNN models

		Precision	Recall	F1 score
Vgg16 Net	Covid 19	0.96	0.98	0.97
	Normal	0.94	0.99	0.96
	Viral pneumonia	0.98	0.93	0.96
	Accuracy			0.96
	Macro avg	0.96	0.96	0.96
	Weight avg	0.96	0.96	0.96
ResNet 50	Covid 19	1.00	0.95	0.98
	Normal	0.94	1.00	0.97
	Viral pneumonia	1.00	0.94	0.97
	Accuracy			0.97
	Macro avg	0.98	0.97	0.97
	Weight avg	0.97	0.97	0.97
GoogleNet	Covid 19	1.00	0.86	0.93
	Normal	0.96	0.96	0.96
	Viral pneumonia	0.94	0.96	0.95
	Accuracy			0.95
	Macro avg	0.97	0.93	0.94
	Weight avg	0.95	0.95	0.95

Table 2. Performance of models

accuracy	0.9587	0.9690	0.9518
sensitivity	0.9773	0.9545	0.8636
specificity	0.9963	1.0000	1.0000

IV. Conclusion

With the algorithm using VGG-16 network structure, accuracy (acc) = 95.87%; With the algorithm using ResNet network structure, accuracy (acc) = 96.90%; With the algorithm using the GoogleNet network structure, accuracy (acc) was calculated as 95.18%. The deep learning algorithms designed have a high rate of success for the diagnosis of COVID-19 coronavirus disease.

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