Deep-COVID-19: Deep Learning for COVID-19 Detection from X-ray Images

Ahmed Hashem El Fiky

Abstract*: *The COVID-19 will take place for the first time in December 2019 in Wuhan, China. After that, the virus spread all over the world, with over 4.7 million confirmed cases and over 315000 deaths as of the time of writing this report. Radiologists can employ machine learning algorithms developed on radiography pictures as a decision support mechanism to help them speed up the diagnostic process. The goal of this study is to conduct a quantitative evaluation of six off-the-shelf convolutional neural networks (CNNs) for COVID-19 X-ray image analysis. Due to the limited amount of images available for analysis, the CNN transfer learning approach was used. We also developed a simple CNN architecture with a modest number of parameters that does a good job of differentiating COVID-19 from regular X-rays. in this paper, we are used large dataset which contained CXR images of normal patients and patients with COVID-19. the number of CXR images for normal patients are 10,192 image and the number of CXR images for COVID-19 patients are 3,616 images. The results of experiments show the effectiveness and robustness of Deep-COVID-19 and pretrained models like VGG16, VGG19, and MobileNets. Our proposed Model Deep-COVID-19 achieved over 94.5% accuracy.

Keywords*: *Coronavirus; Convolution Neural Networks; Deep-Learning; Covid-19.

I. INTRODUCTION

The current coronavirus disease pandemic (COVID-19) is particularly concerning, as the second wave appears to be significantly more dangerous than the first. India is one of the most impacted countries in the second wave of the severe acute respiratory syndrome coronavirus 2. (SARS-CoV-2). The US and Brazil are also at risk, as they are still recovering from the previous wave. On April 26, 2021, India's total number of infected people was 360,960, and it continues to rise [1]. This is worrying for Bangladesh because the Indian strain of SARS-CoV-2 is more dangerous than the other forms due to their close geographical closeness. The virus is rapidly spreading and can be passed on to persons of all ages, resulting in severe illness. COVID-19, a highly contagious viral disease caused by SARS-CoV-2, has killed over 2.9 million people globally, making it the biggest global health event since the 1918 influenza pandemic. Patients above the age of 60, as well as those with medical problems, should be considered at a higher risk of contracting SARS-CoV-2 [2]. According to the World Health Organization, there are approximately 167,011,807 COVID-19 cases globally [3]. When this virus infects the human body, there are two possible outcomes: moderate and severe. When a coronavirus infection starts, one thing is certain: the virus has a negative impact on lung health. As a result, doctors advise patients to use an oxygen meter to monitor their oxygen levels so that any anomalies can be detected and treated early [4]. Convolutional neural networks (CNNs) are suitable for this type of challenge [5]. The virus usually affects the lungs in humans, causing pneumonia in severe cases. As a result, the oxygen level in the body plummets. Because there is presently no cure for this virus, the only way to prevent it from spreading is to develop a vaccine. As a result, the only alternative so far has been testing and tracing. In most cases, in medical research, the polymerase chain reaction (PCR) test is used. However, due to the time and cost needed, completing enough PCR testing has become nearly impossible as the number of cases continues to rise. As a result, alternative testing is required to quickly identify infected individuals and place them in quarantine or isolation. To date, some deep learning approaches have been used to detect infections. On the other hand, the results of these deep learning approaches are insufficient for dealing with a medical diagnosis system. Because of their architectural flexibility and capacity to handle highly non-linear systems, neural networks are now widely used in a range of applications. We provide Deep-COVID-19, a deep learning neural network architecture for COVID-19 detection, in this paper. The following are some of our contributions:

- We are conducting a comprehensive assessment with rigorous beta setup to assess Deep-COVID-19's performance with large dataset of Covid-19 patients and normal patients' images which available to the public in the real world (COVID-19 Radiography Database [6]).
- Deep-COVID-19 provides low false positive rate, high true positive rate and high accuracy based on deep learning neural network framework.

The rest of the paper is laid out as follows. Section 2 discusses relevant papers, whereas Section 3 presents the proposed model. The findings and analysis are reported in Section 4, and the conclusions are offered in Section 5.

II. RELATED WORK

Since the COVID-19 outbreak, researchers have concentrated their efforts on developing a vaccine [7] and identifying COVID-19 using PCR and imaging techniques [8].

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We examine research into how radiography images could aid and complement PCR in the diagnosis of COVID-19 cases. Ali et al. [8] developed a deep convolutional neural network (CNN) based on ResNet50, InceptionV3, and Inception-ResNetV2 models to classify COVID-19 Chest X-ray images into normal and COVID-19 classes. The CT scan results, and the PCR method had a good correlation, they discovered. The chest X-ray pictures of 50 COVID-19 patients were extracted from [9]'s open source GitHub repository. Prabira et al. [10] proposed a method to detect COVID-19 utilising X-ray images using deep feature and support vector machines (SVM). They gathered X-ray images using GitHub, Kaggle, and the Open-I repository. Despite the small amount of photographs utilised in their research, they were able to extract the deep feature maps of many CNN models and conclude that ResNet50 outperforms them. Maghdid et al. [11] proposed a basic 16-layer CNN for COVID-19 identification and achieved good results using both X-ray and CT images, however the dataset used was small. Xiaowei et al. [12] created an early prediction model employing the Resnet18 model and image patches concentrating on regions of interest to identify COVID-19 pneumonia from Influenza-A viral pneumonia and healthy cases using lung CT images. With 86.7% CT scans, the CNN model achieved the highest accuracy. Shuai et al. [13] used CT images to predict COVID-19 patients, achieving an accuracy of 89.5%, a specificity of 88.0%, and a sensitivity of 87.0% using the Inception transfer-learning model.

Wang and Wong [14] studied the COVIDx dataset and the COVID-Net neural network architecture for detecting COVID-19 instances in open-source chest X-ray radiography pictures. Normal X-rays, Bacterial X-rays, Viral X-rays relevant to non-COVID-19 pneumonia, and COVID-19 X-rays are the four types of chest radiography images in the dataset. They had an overall accuracy of 83.5% for these four classes. Non-COVID-19 had the lowest reported positive predictive value (67.0%), whereas Normal had the highest (95.1%).

III. PROPOSED METHODOLOGY

Deep learning is the most used AI technique for categorization issues right now [15]. It has been successfully used in a variety of applications, particularly in the medical industry. The models utilized in this study are described in the following paragraphs.

1. 2D sequential CN CNN models are a subcategory of deep learning models. They're a type of feedforward neural network that's been discovered to be particularly effective at interpreting multidimensional data (such as photos) [16]. CNNs, on the other hand, save memory in comparison to multilayer perceptron's by sharing parameters and employing sparse connections. The incoming images are turned into a matrix that the various CNN parts can process. The model is made up of various convolution and pooling layers that alternate (see Figure 1 and Table 1):

Convolutional layer

The convolutional layer determines the characteristics of the numerous patterns in the input. It's made up of a succession of convolutions (dot products) that are applied to the input matrix. This stage creates a feature map by combining a number of filters into an image processing kernel (i.e., motifs). The input is divided into small windows called receptive fields, which are convolved with the kernel using weights. In this work, a 2D convolution layer was used (i.e., using the CONV2D class).

Batch Normalization

It is the technique of adding extra layers to a deep neural network to make it faster and more stable. The standardizing and normalizing procedures are performed by the new layer on the input of a previous layer.

Pooling layer

This down-sampling layer reduces the output volume's spatial dimensions by reducing the amount of feature mappings and network parameters. Pooling also improves the generalization of the model by reducing overfitting [17]. This stage generates a collection of characteristics that are unaffected by translational shifts and distortions [18].

Fully connected layer

This layer takes the feature map as input and generates nonlinear changed output using an activation function. This is a multi-stage strategy that combines features from all phases to build a nonlinear collection of categorization features. The rectified linear unit (ReLU), which facilitates in the resolution of the vanishing gradient problem [19], was used in this phase.

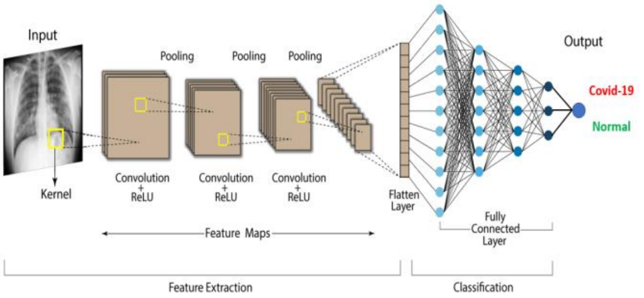

Figure1: Deep-COVID-19 System Architecture

2. Pre-trained Models

Mobile Nets

The MobileNets model [20] is a resource-constrained CNN architecture that was used in this study with the goal of developing future mobile disease detection applications. It uses depth-wise separable convolutions, which drastically reduces the number of parameters. MobileNets is an open-source project developed by Google to assist developers in creating low-power, compact, and low-latency mobile applications.

Table1: Summary of CNN model used in this work

Layer	Output Shape	No. of Parameters
CONV2D-1	(None,200,200,32)	896
BatchNormalization-1	(None,200,200,32)	128
MaxPooling2D-1	(None,100,100,32)	0
CONV2D-2	(None,100,100,32)	9248
BatchNormalization-2	(None,100,100,32)	128
MaxPooling2D-2	(None,50,50,32)	0
CONV2D-3	(None,50,50,32)	9248
BatchNormalization-3	(None,50,50,32)	128
MaxPooling2D-3	(None,25,25,32)	0
CONV2D-4	(None,25,25,64)	51264
BatchNormalization-4	(None,25,25,64)	256

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MaxPooling2D-4	(None,12,12,64)	0
CONV2D-5	(None,12,12,64)	102464
BatchNormalization-5	(None,12,12,64)	256
MaxPooling2D-5	(None,6,6,64)	0
CONV2D-6	(None,6,6,64)	102464
BatchNormalization-6	(None,6,6,64)	256
MaxPooling2D-6	(None,3,3,64)	0
Flatten	(None,576)	0
Dense	(None,256)	147712
Dense-1	(None,1)	257

VGG-16

Numerous models have been proposed in the literature, including VGG-16 [21]. It has undergone multiple changes to improve accuracy and resource efficiency (e.g., VGG-19). The VGG model is a 19-layer spatial exploitation CNN with three-by-three filters (computability), one-by-one convolution between convolution layers (for regularization), and max-pooling after the convolution layer. The model's simplicity is well-known [16]. (Refer to Figure 2)

VGG-19

VGG-19 is a 19-layer deep convolutional neural network. The ImageNet database [22] has a pretrained version of the network that has been trained on over a million photos. The network can classify photos into 1000 different object categories, including keyboards, mice, pencils, and a variety of animals. As a result, the network has learned a variety of rich feature representations for a variety of images.

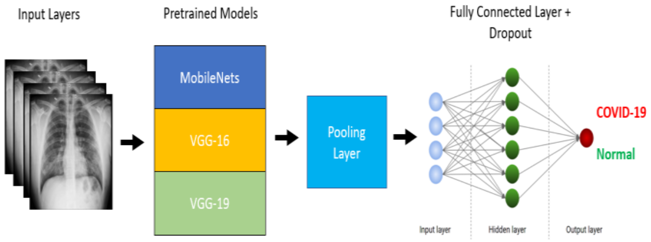

Figure 2: System Architecture of Pretrained models

IV. EXPERIMENTAL & RESULTS

A. Dataset Description

Images of CXR from two classes were included in the collection. CXR images of COVID-19 patients are stored in one class, whereas CXR images of normal patients are stored in the other. These classes were split into two groups. One is a validation set, while the other is a training set. There were 13,808 photos in the dataset [6]. The dataset was split into training and test sets in this study, with 80% of the training data and 20% of the test data being used. Without gathering new data, data augmentation has been used to expand the diversity of the data. The CXR pictures of a COVID-19 patient and a normal patient are shown in Figures 3 and 4, respectively.

Figure 3 displays a CXR image altered by SARS-CoV-2, while Figure 4 shows a normal CXR image.

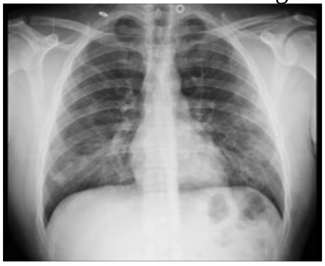

Figure 3: X-ray image of a COVID-19 Patient

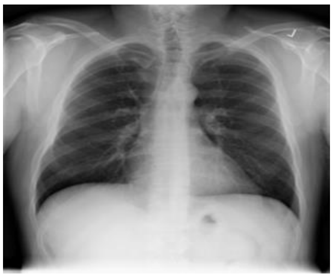

Figure 4: X-ray image of a normal Patient

B. Model Evaluation Metrics

Log loss is employed as an evaluation measure in the proposed Model. The cross-entropy between correct and predicted labels is known as log loss. The following is the exact formula for calculating log loss:

$$logloss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log(\rho_{ij})$$

Here, N is the number of samples and M is the number of classes. y represents the true label of the class and ρ is the probability of the given sample. A log that is mentioned in the above formula is Natural Logarithm.

Accuracy is another evaluation measure used for evaluating the performance of the proposed model mathematically accuracy can be defined as below:

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

In the above equation, TP and TN are the number of positive and negative samples, respectively which are correctly classified by the classifiers. Whilst, FP and FN are the number of positive and negative samples, respectively, which are misclassified by the classifiers.

C. Experimental Design

The proposed model is a sequential neural network. We used the “ReLu” activation function in the hidden layer and the “Sigmoid” function in the output layer. 'Adam' and 'binary entropy' were used to improve the loss function respectively.

Experiments were performed on a HP EliteBook at a speed of 2.4 GHz Intel Core i5 with 8.0 GB RAM. We implemented our experiment with the Keras framework in Python 3.7.

D. Experimental Results

The results of our proposed model Deep-COVID-19 compared with the other pretrained models which are VGG16, VGG19, and MobileNets. A logloss and Accuracy were used to evaluate the performance of the models.

1) Performance evaluation of our proposed model:

Our proposed model Deep-COVID-19 trained for 5 epochs with an early stop. All models were trained on 80% of the dataset and Deep-COVID-19 tested on the remaining 20% of the dataset. The Figure 5 shows the relation between No. of epochs and loss value. The training loss and validation loss are stood at 0.34 and 1.51 respectively at 1st epoch. In the contrast, the training loss decreased sharply to 0.22 at 2nd epoch. Then the validation loss decreased sharply to 0.65 at 2nd epoch too.

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Finally, the training loss and validation loss decreased gradually to 0.13 and 0.18 respectively at 5th epoch. The Figure 6 shows the relation between No. of epochs and accuracy value. The training accuracy and validation accuracy are stood at 0.8498 and 0.2634 respectively at 1st epoch. In the contrast, the training accuracy increased dramatically to 0.9121 at 2nd epoch. Then the validation accuracy increased gradually to 0.7003 at 2nd epoch too. Finally, the training accuracy and validation accuracy increased to 0.9491 and 0.9419 respectively at 5th epoch.

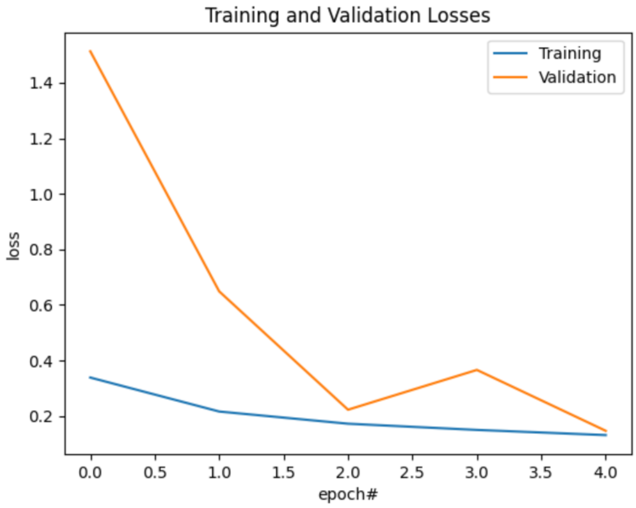

Figure 5: model loss of our proposed model

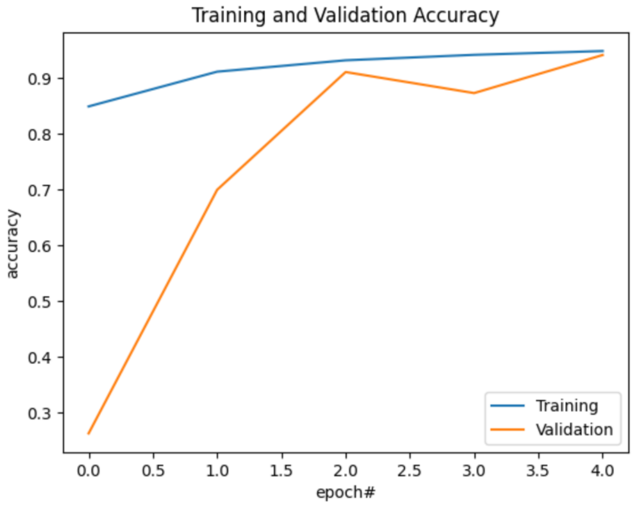

Figure 6: model accuracy of our proposed model

2) Performance evaluation of pretrained model VGG16:

In this pretrained model VGG16 trained for 5 epochs with an early stop. The Figure 7 shows the relation between No. of epochs and loss value. The training loss and validation loss are stood at 0.50 and 0.40 respectively at 1st epoch. In the contrast, the training loss decreased sharply to 0.39 at 2nd epoch. Then the validation loss decreased sharply to 0.32 at 2nd epoch too. Finally, the training loss decreased gradually to 0.26. whilst the validation loss decreased to 0.24 at 4th epoch and fixed with this value to 5th epoch.

The Figure 8 shows the relation between No. of epochs and accuracy value. The training accuracy and validation accuracy are stood at 0.7480 and 0.8090 respectively at 1st epoch. In the contrast, the training accuracy increased dramatically to 0.8295 at 2nd epoch. Then the validation accuracy increased gradually to 0.8790 at 2nd epoch too. Finally, the training accuracy increased dramatically to 0.90 at 5th epoch. Whilst the validation accuracy fixed to 0.91 from the 4th epoch until the 5th epoch.

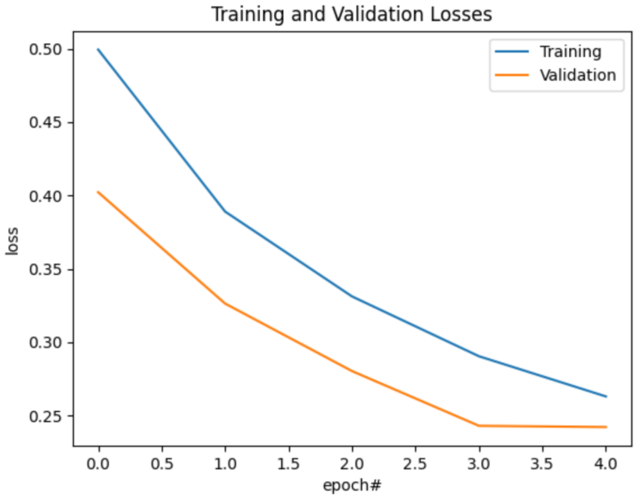

Figure 7: model loss of pretrained model VGG16

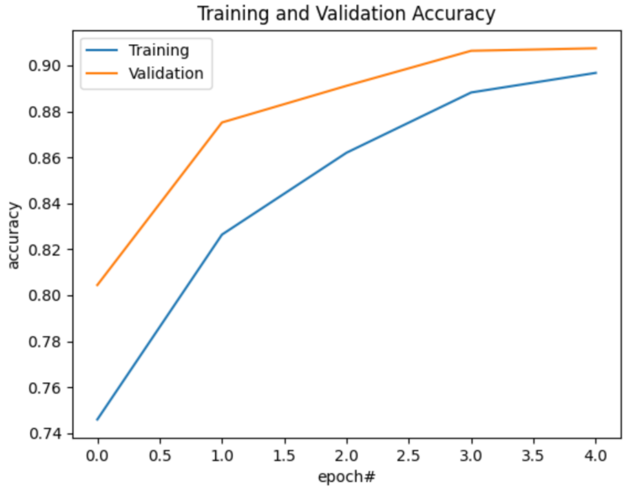

Figure 8: model accuracy of pretrained model VGG16

3) Performance evaluation of pretrained model VGG19:

In this pretrained model VGG19 trained for 5 epochs with an early stop. The Figure 9 shows the relation between No. of epochs and loss value. The training loss and validation loss are stood at 0.48 and 0.39 respectively at 1st epoch. In the contrast, the training loss decreased sharply to 0.42 at 2nd epoch. Then the validation loss decreased sharply to 0.335 at 2nd epoch too. Finally, the training loss decreased gradually to 0.35 at 5th epoch. whilst the validation loss decreased sharply to 0.305 at 5th epoch too. The Figure 10 shows the relation between No. of epochs and accuracy value. The training accuracy and validation accuracy are stood at 0.75 and 0.8195 respectively at 1st epoch. In the contrast, the training accuracy increased dramatically to 0.798 at 2nd epoch.

Then the validation accuracy increased gradually to 0.86 at 2nd epoch too. Finally, the training accuracy and the validation accuracy increased dramatically to 0.849 and 0.88 respectively at 5th epoch.

4) Performance evaluation of pretrained model MobileNets:

In this pretrained model MobileNets trained for 5 epochs with an early stop. The Figure 11 shows the relation between No. of epochs and loss value. The training loss and validation loss are stood at 0.4256 and 0.2718 respectively at 1st epoch. In the contrast, the training loss decreased sharply to 0.2969 at 2nd epoch. Then the validation loss decreased sharply to 0.2263 at 2nd epoch too. Finally, the training loss decreased gradually to 0.1855. Whilst the validation loss decreased to 0.1979 at 3rd epoch and decreased to 0.1829 at 5th epoch.

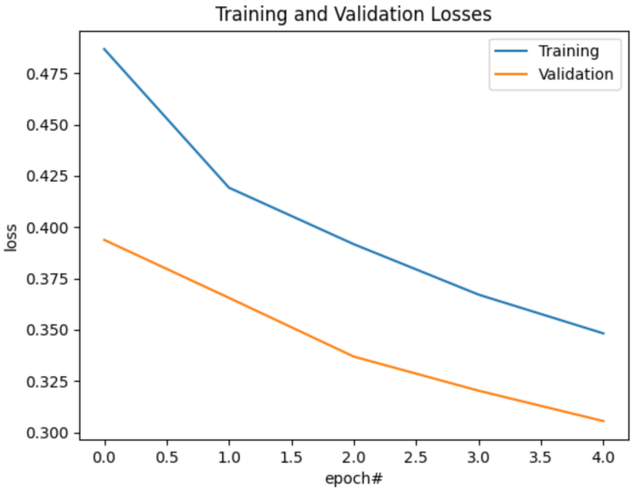

Figure 9: model loss of pretrained model VGG19

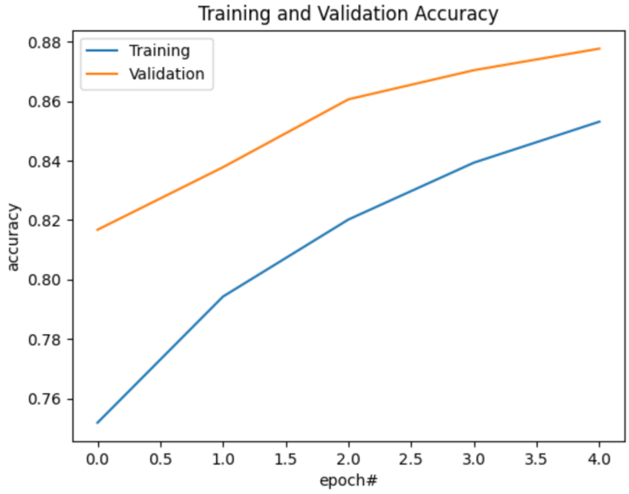

Figure 10: model accuracy of pretrained model VGG19

The Figure 12 shows the relation between No. of epochs and accuracy value. The training accuracy and validation accuracy are stood at 0.8135 and 0.8930 respectively at 1st epoch. In the contrast, the training accuracy increased dramatically to 0.8804 at 2nd epoch. Then the validation accuracy increased gradually to 0.9180 at 2nd epoch too. Finally, the training accuracy and the validation accuracy increased dramatically to 0.9271 and 0.9292 respectively at 5th epoch.

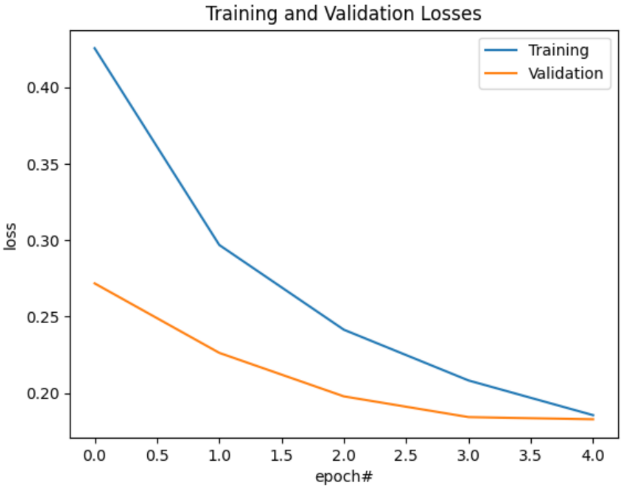

Figure 11: model loss of pretrained model MobileNets

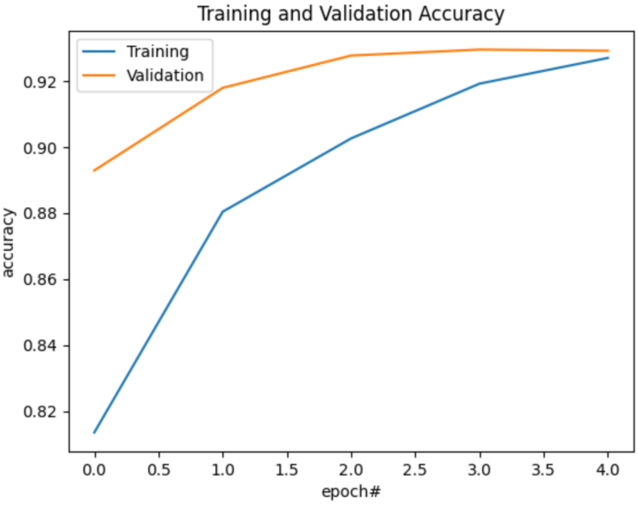

Figure 12: model accuracy of pretrained model MobileNets

V. CONCLUSION

This research provided a critical evaluation of three off-the-shelf CNN architectures, which were originally proposed for natural image processing, with the goal of assisting radiologists in distinguishing COVID-19 disease based on chest X-ray pictures. We also introduced Deep-COVID-19, a simple CNN architecture that beat other pretrained models VGG16, VGG19, and MobileNets in detecting COVID-19 Patients from normal patients with 95 % accuracy. Segmenting the lung region from chest X-rays and eliminating additional artefacts such as text and medical device traces from chest X-rays are among the future research goals and ongoing study.

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