Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 50, No. 1, 2024, pp. 133-143
DOI: https://doi.org/10.25195/ijci.v50i1.436
Print ISSN: 2313-190X, Online ISSN: 2520-4912

Research Article

Detection of Covid-19 and chest pneumonia based on X-ray images using Deep-Transfer Learning

Nashwan Amin Al-khulaidi [1,*]
Faculty of Engineering and Information Technology
Taiz University.Taiz, Yemen.
nashwan1email@gmail.com

Mohammed Hashem Almourish [2]
Faculty of Engineering and Information Technology
Taiz University, Taiz, Yemen.
Faculty of Engineering & Technolog,
Philadelphia University, Amman,Jordan
malmourish@philadelphia.edu.j o

Abdulrhman Mohammed Ali [3]
Faculty of Engineering and Information Technology
Taiz University.Taiz, Yemen.
abood.alsh2021@gmail.com

ARTICLEINFO
Article History
Received: 29/09/2023
Accepted: 01/12/2023
Published: 28/06/2024

ABSTRACT
Numerous people have died as a result of the coronavirus outbreak in 2019 (COVID-19), which also affected millions of others around worldwide. The infection spreads quickly. Therefore, technology that enables quick virus detection will offer healthcare professionals much-needed assistance. This study aims to identify COVID-19 disease from X-ray images of healthy and infected people with pneumonia by using a modified VGG16 model. The proposed model achieved better results than previous studies presented with an accuracy of 99.13%, a recall of 99% and precision of 98.70%.

Keywords: ***COVID-19, Deep-Transfer Learning, X-ray images.***

1. INTRODUCTION

End of 2019 saw the emergence of COVID-19 disease in China. Early on in the illness, serious respiratory consequences occur. There were heart impairments, pulmonary issues, and other consequences. The Intensive Care Unit (ICU) was required to handle a large number of infected patients [1].

In order to stop the spread of the virus, it was crucial to find a quick, cheap, accessible, and reliable technique to identify the infection.

One of methods for diagnosing COVID-19 is reverse transcriptase quantitative polymerase chain reaction (RT-qPCR) testing [2]. Small amounts of viral Ribonucleic acid (RNA) will be tested by nasal swaps, amplified, and quantified, with virus identification visually indicated by a fluorescent dye. Unfortunately, the RT-qPCR test is manual, time-consuming, and results can take up to two days. It is not an automated process. False positive PCR testing has also been demonstrated in several investigations [3]. Other testing techniques include X-ray imaging- and computed tomography (CT) imaging-based technologies [4,5]. The process of detecting COVID-19 using CT scans requires hard work and specialists [6,7]. Both the PCR tests and CT scans are comparatively costly [8, 9] and with high demand many countries are forced to perform selective testing for only high risk population.

X-ray imaging is typically used to identify lung infections since it is relatively inexpensive [10]. Medical professionals and treating physicians of the COVID-19 dataset [11] patients conducted medical observations. The common characteristics seen in COVID-19 patients' X-Ray images include a patchy infiltration that resembles the symptoms of other viral pneumonias. Early COVID-19 abnormalities are not visible on X-rays, but as the disease worsens, the virus gradually manifests as a typical unilateral irregular penetration involving the mid-upper zone or lower zone of the lungs, infrequently with signs of consolidation. Computer vision diagnostic techniques from X-ray images give clinicians an automated "second reading" that aids in the diagnosis of the virus and advances the global war on viruses. Only using X-Ray images typically make it difficult to distinguish between COVID-19 pneumonia and

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other types of pneumonia (viral and bacterial) [12]. Deep transfer learning is used to identify pediatric pneumonia from chest X-ray images, and the type of lung nodules from CT images, among other things [13,14].

In this study a modified VGG16 model is used to identify COVID-19 disease from X-ray images of healthy and infected people with pneumonia.

The rest of this study is arranged as follows: In the second section the relevant literature on disease recognition and the techniques used are discussed. While in the third section, the proposed methodology for identifying Covid 19 disease through X-ray images was presented, and the results were presented in the fourth section. The last section presented the conclusion of this paper.

2. LITERATURE REVIEW

In the 1960s, researchers and clinicians began using computers to help them identify and classify pulmonary diseases based on X-Ray images. Studies on a variety of illnesses, such as osteoporosis [15], breast cancer [16], and heart disease [17], showed extremely precise identification as this field progressed over the next years. Because soft tissues were difficult to discern in X-Ray images due to a lack of contrast, several researchers focused on contrast enhancement [18] as an essential step in X-Ray-based diagnosis. An important stage in the detection of lung nodules is the segmentation of the lung in X-ray images. The literature predicts many segmentation techniques based on linear filtering/thresholding, rolling ball filters, and most recently CNNs [19].

Five pre-trained models (ResNet-50, ResNet-101, AlexNet, VGG11, and SqueezeNetV-1.0) were suggested to diagnose Covid-19 based on CT scans. ResNet-50 has an accuracy of 93.2% and the best loss rate of (0.22) [20]. Several state-of-the-art deep learning models, including DenseNet201, Resnet50V2, and Inceptionv3, were individually enhanced in [21] to produce independent predictions, then; they were combined using a weighted average ensemble technique to reach a classification accuracy of 91:62%. Reference [22] used tomography of the lung to identify the COVID-19 disease, and a three-dimensional CNN network was proposed, with a classification accuracy of 86.7%.The authors in [23] proposed using the COVID-Net and the COVIDx dataset to identify COVID-19.

The authors confirmed in [24] that the method of analyzing images with artificial intelligence to identify COVID-19 achieves results with high accuracy, and the disease can be identified and tracked. While the authors in [25] used X-ray images and parallel-dilated CNN to develop the innovative PDCOVIDNet architecture. They were able to acquire and extend all the necessary features in the suggested technique to obtain a detection accuracy of 96.58% by using a dilated convolution in the parallel stack. In [26] a deep convolutional neural network termed Disassemble, Transfer and Composition (DeTraC) was proposed to identify COVID-19 disease from chest X-ray images. To investigate class boundaries to search for anomalies in the dataset, an analysis strategy was proposed to achieve high levels of accuracy (93.1%). and sensitivity (100%). A deep learning technique based on the ResNet-101 model was used to identify COVID-19 by chest X-ray images. This approach had receiver operating curve, sensitivity, specificity, and accuracy of 0.82, 77.3%, 71.8%, and 71.9%, respectively [27].

The study [28] presented three layers: (a) patient layer, (b) withdrawal layer, (c) hospital layer. The data was collected in the patient layer, and then a fuzzy network structure was proposed to process the data and then passed to the proposed deep learning model in the hospital layer based on the detection of COVID-19 based on X-ray images. This technique achieved an accuracy of 97.95% and a specificity of 98.85%.

In [29] COVID-19 was classified using a deep learning-based decision tree classifier using chest X-ray images. This classifier compared three binary decision trees based on the PyTorch frame. The third decision tree has an average classification accuracy of 95% for chest X-ray images.

In the model developed to dynamically optimize the weight ratio, ResNet-101 and ResNet-151 were merged with fusion effects. Three kinds of chest X-rays were used to classify the images: normal, COVID-19, and viral pneumonia. During the testing phase, accuracy of 96.1% was reached [30]. Reference [31] proposed a deep neural network to determine disease severity and used 729 CT scans of COVID-19 patients and achieved an accuracy of 95.34%.

In [32] four CNNs (ResNet18, ResNet50, SqueezeNet, and DenseNet-121) were proposed, and the results were specificity of 92.9% and sensitivity of about 98%. ResNet50 achieved an accuracy rate of 98% in identifying COVID-19 using the dataset of which are 50 COVID-19 cases and 50 controls [33]. CNN deep networks showed effectiveness in identifying cases of pneumonia by normal and abnormal chest radiographs with an accuracy of 94.64% [34] while VGG16 CNN and Resnet50 networks showed effectiveness in diagnosing COVID-19 with an accuracy of 89.2% [35].

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The study [36] used eight deep learning models to identify COVID-19 and 400 chest X-rays were used and NasNetMobile achieved the best results with an accuracy of 93.94%.While the study [37] used seven different CNN models to identify COVID-19. From the results, the DenseNet model and the VGG19 model achieved the best results, with F1 scores of 0.89 and 0.91, respectively.

In [38], the Darknet model has high accuracy for binary classification of 98% and 87% for multiclass classification to identify COVID-19 for 127 patients with the disease. In [39], an automated system for COVID screening was presented and it was conducted for 2088 chest X-ray images and it is based on five supervised reference classification algorithms that are carried out in two stages of classification and achieved high results in both stages. Reference [40] used convolutional neural network to identify COVID-19 by using CT scan images. COVID19 was diagnosed using the CNN model with various filters, and the best accuracy achieved was 88.15%.

In [41], a multi-class CNN was proposed to classify X-ray images into normal, COVID-19, and pneumonia images. The accuracy of the multi-class CNN model is 93.75%. Reference [42], developed two models for classification (COVID-19, pneumonia, and normal patients). The first model combines a CNN with XGBoost and the second model utilizes a classical stand-alone CNN. The hybrid model (CNN with XGBoost) achieved the best results with an accuracy of 99.04%. Table 1 presents previous studies.

TABLE 1: PREVIOUS STUDIES

Study	Method Used	DataSet	Accuracy %
Almourish et al. [20]	AlexNet, VGG11, ResNet-50, ResNet-101, and SqueezeNetV-1.0	746 samples	91
Sethy and Behra [21]	DenseNet201, Resnet50V2 and Inceptionv3	6910 samples	91.62
Xiaowei Xu et al. [22]	Deep CNN	8830 samples	86.7
Shuai Wang et al. [23]	Deep CNN	9312 samples	89.5
Ref [24]	Deep CNN	13,800 samples	92.6
Chowdhury et al. [25]	Deep CNN	12,000 samples	96.58
Abbas et al. [26]	Deep CNN	5,000 samples	93.1
Azemin et al. [27]	ResNet-101	2088 samples	91.33
El-Rashidy et al. [28]	CNN	7,800 samples	97.9
Yoo et al. [29]	CNN	3,300 samples	95
Wang et al. [30]	ResNet-101 and ResNet-151	12,000 samples	96.1
Yu et al. [31]	pretrained deep neural network	11,920 samples	95.34
Minaee, S[32]	ResNet18, ResNet50, SqueezeNet, and DenseNet-121	5184 samples	92.9
Narin, A. [33]	ResNet50, InceptionV3, and InceptionRes-NetV2	100 samples	98
Tang, Y.-X.[34]	deep CNNs	21,152 samples	94.64
Hall, L.O[35]	VGG16 + Resnet50	204 samples	89.2
Ahsan, M.[36]	NasNetMobile	400 samples	93.94
Hemdan, E.El[37]	VGG19, Xception, ResNetV2, DenseNet201, InceptionV3, MobileNetV2, InceptionResNetV2	750 samples	91
Ozturk, T.[38]	Modified Darknet	1127 samples	98
Chandra, T.B[39]	ACoS system	2356 samples	91.33
Praveen Tumuluru; et al. [40]	Deep CNN		88.15
Rubina Sarki, et al. [41]	multi-class CNN	296 samples	93.75
Aphelele Dumakude andAbsalom E. Ezugwu [42]	Conventional CNN architecture as a feature extractor with XGBoost as the classifier	2905 samples	99.04
Our model	**Vgg16**	**15000 samples**	**99.13**

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3. Methodology

A model has been proposed to identify COVID-19 disease from healthy people as well as those who have suffered from pneumonia through x-ray images.

The identification process consists of three main stages: collecting the data set, pre-treatment of the data set, and then using the proposed VGG16 model to classify the cases into healthy, sick with pneumonia and infected with COVID-19.

A. Dataset Collection

In this study, dataset was collected from chest X-ray images from healthy people and patients with pneumonia and COVID-19. In order to create the dataset, we collected eleven accessible and open source sub-datasets [43-52]. All images in the sources were combined to form a single dataset. As shown in Table II, the database in this study includes 5000 images of COVID-19, 5000 images of pneumonia patients, and 5000 images of healthy people.

TABLE II: DATASET OF THE STUDY

Classes	Images	Datasets
Normal	5000 images	[43]
Pneumonia	5000 images	[44-45]
Covid-19	4420 images (5000 after data augmentation)	[45-52]
Total	15000 images	

B. Data Pre-processing

Pre-processing data is very importance for all data because it makes them suitable and ready for implementation. Therefore, we change the size of the data set images to (224.224.3) because the VGG-16 model only accepts this size of images in order to make training faster.

C. The Proposed Model

The VGG16 learning transfer model has been proposed on our COVID-19 dataset and has been trained and tested on available images. VGG16 is a deep convolutional neural network (CNN) architecture consisting of 16 convolutional layers. This depth allows the capture of complex and hierarchical patterns in lung images, which are essential for accurate detection of Covid-19. The complexity of the VGG16 architecture enables it to learn highly discriminative features from the data, which contributes to improved accuracy.

In the VGG16 architecture, the network is organized into blocks of convolutional layers, followed by max-pooling layers. The number of blocks and their configurations are as follows:

- **Block 1:**

Convolutional layers: Two 3x3 filters with 64 output channels each.

Max-pooling layer: 2x2 window with a stride of 2.

Output size: The spatial dimensions of the feature maps are reduced by a factor of 2.

- **Block 2:**

Convolutional layers: Two 3x3 filters with 128 output channels each.

Max-pooling layer: 2x2 window with a stride of 2.

Output size: The spatial dimensions of the feature maps are reduced by a factor of 2.

- **Block 3, Block 4, and Block 5:**

1. Convolutional layers: Three 3x3 filters with 256 output channels each.

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1. Max-pooling layer: 2x2 window with a stride of 2.
2. Output size: The spatial dimensions of the feature maps are reduced by a factor of 2.

After these five blocks, the output of the last max-pooling layer is flattened into a vector and passed through three fully connected layers for classification:

- **Fully Connected Layers:**

- Fully connected layer: 4096 units.
- Fully connected layer: 4096 units.
- Fully connected layer: 1000 units (corresponding to the number of classes in the ImageNet dataset).

To achieve our proposed model, the following steps were implemented: First, preprocessing has been applied to the input dataset, which is an RGB image with a size of 224x224x3, after which it passes through the first and second convolutional layers with 64 filters of size 3x3, and then the dimensions of the resulting image are reduced to 112x112x64. Second, the dataset has been divided into training data and test data. In the training phase, we used 12,000 images, (for validation 15% of the training images have been used) and for testing, we used 3,000 images. Third, the data has been passed to the VGG16 learning transfer model after removing the network's standard output layer, and we add layers specific to the proposed model, which consists of three output classes.

In our proposed model, 5 blocks were frozen, and delete the fully connected of the output layer. Five frozen layers were selected after several training and testing attempts to obtain the best results, and indeed they achieved better results. Freeze Layers keeps some or all of the pre-trained layers constant during the fine-tuning process. In our model, freezing five layers allowed us to preserve the learned representations of the datasets as in the ImageNet dataset that adapted the last layers for COVID-1 detection, and because five layers were frozen, it prevented overfitting, which achieved better performance of the proposed model.

Fourth, a flat layer was added to simplify the representation of dataset data in the form of a matrix with sequential values, and a drop-down layer was also added to randomly reset the input data for the layer in the training phase, it also increases the input data by a factor so that it is proportional to the inputs for the next layer.

Fifth, we add three layers to the output that represent the classes of our model, which are two layers of (Dense (128, activation='relu')) and one layer of (Dense (3, activation='softmax')), where the activation functions relu and softmax determine the outputs of the model by activating the passed data.

Finally, we trained and measured the performance of the proposed model. Four measures were used to measure the performance of the VGG-16 model (accuracy, recall, precision and AUC). Figure 1 shows the steps of the proposed VGG16 model for identification of COVID-19 disease.

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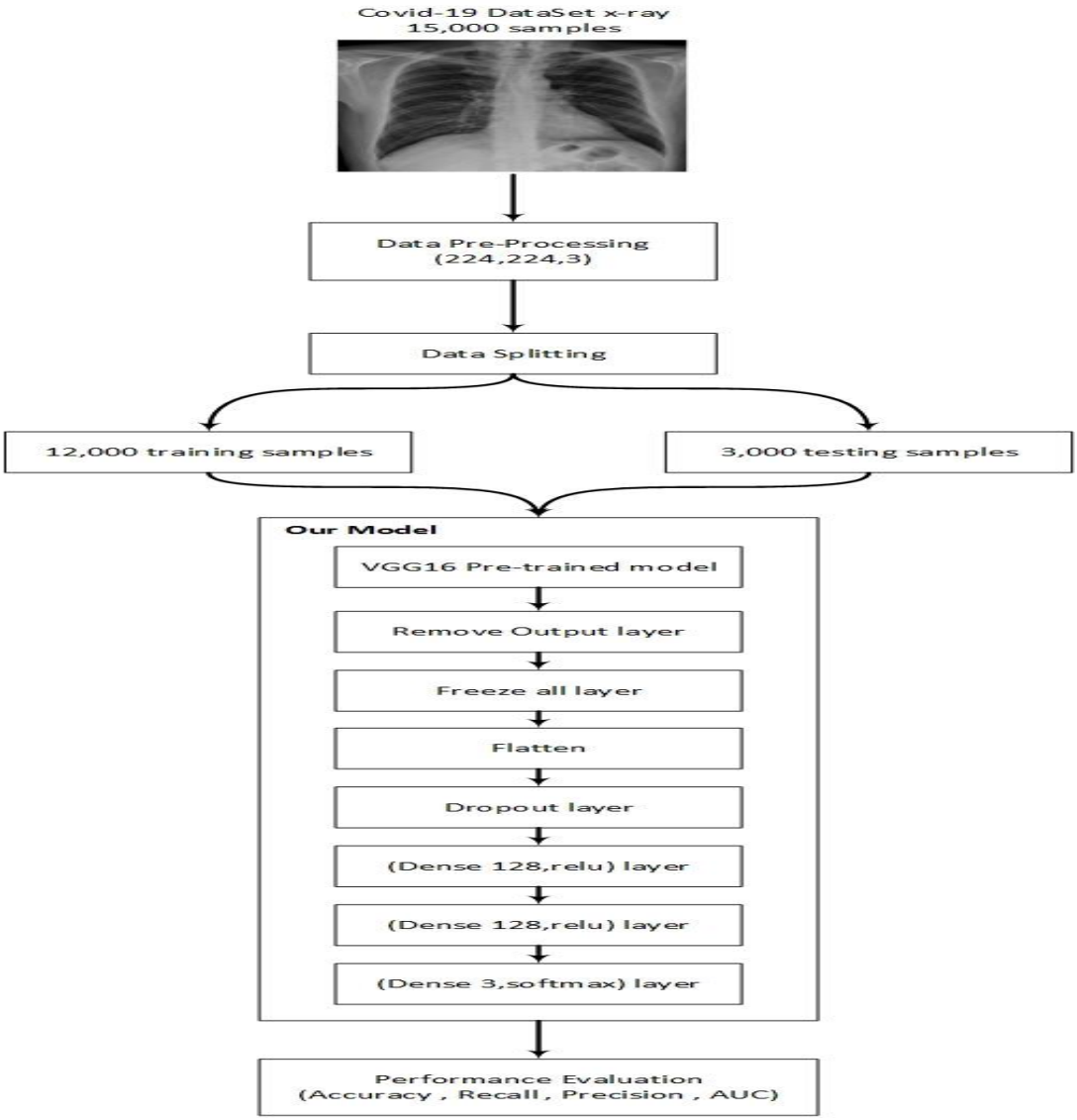

Fig. 1. Proposed Model

4. Result and Discussion

This part presents the obtained results after applying the proposed model, where the dataset was divided into 80% for training, the validation set is 15% of the 80% training set, and 20% for testing.

To measure performance of the modified VGG-16 model in this study, four measures were used: accuracy, recall, precision and AUC. A detailed description of these measures follows.

Accuracy, measures the percentage of correct predictions made by the system, as shown in Equation

$$Accuracy = \frac{(True\ positives + True\ Negatives)}{(True\ positives + True\ negatives + False\ positives + False\ negatives)} \quad (1)$$

Recall (sensitivity), measures the ability of the system to identify correctly all X-rays images that have the disease as shown in Equation (2).

$$Recall\ = \frac{True\ positives}{(True\ positives + False\ negative\ )} \quad (2)$$

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Precision measures the proportion of true positive predictions among all the positive predictions made by the system (see equation 3).

$$Precision = \frac{True\ positives}{(True\ positives + False\ positives)} \quad (3)$$

The AUC represents the overall performance of the system. The results of this paper are shown in Table 3, while Figure (2) displays the confusion matrix.

TABLE III: PERFORMANCE METRICS

	Accuracy	loss	Recall	Precision	AUC
train	0.9938	0.02	0.9908	0.9908	0.9996
validation	0.9913	0.05	0.99	0.9870	0.9975

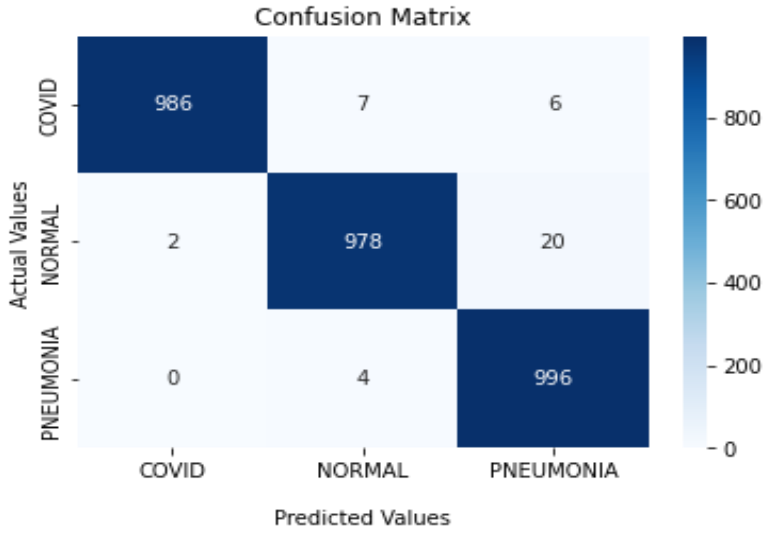

Fig. 2. Confusion Matrix

The modified VGG-16 model was trained in 20 epochs and batch size of 64, and for improvement, the Adam optimizer was used. Python language was used to implement the proposed model. Our model took advantage of transfer learning from pre-training on a large-scale ImageNet dataset. This pre-training enables the model to learn general-purpose visual features that can be applied to various computer vision tasks. By fine-tuning VGG16 in the COVID-19 detection task, we effectively transferred the representations learned from ImageNet, which likely contributed to the high accuracy of our model. VGG16 has shown excellent performance on several computer vision benchmarks, including ImageNet challenges. The ability of architecture to capture and learn rich feature representations from complex images has been demonstrated. By choosing the VGG16 network, we harnessed its ability to extract meaningful features from lung images, which resulted in improved accuracy compared to other models in this field.

In addition, the Trainable parameter plays an important role in improving the network's performance and accuracy, as it determines the weights that change during the training phase to reach the best weights for the network, while the Non-Trainable parameter determines the weights that do not change during the training phase. We obtained the following values for these Trainable Parameters: 3,228,291 and Non-Trainable Parameters: 14,714,688. This model achieved 99.38% training accuracy and 99.13% validation accuracy, the training error rate is 0.0254 and the validation error rate is 0.0511. The best validation accuracy and the lowest error rate occurred in epoch 15, as shown in Figures (3, 4).

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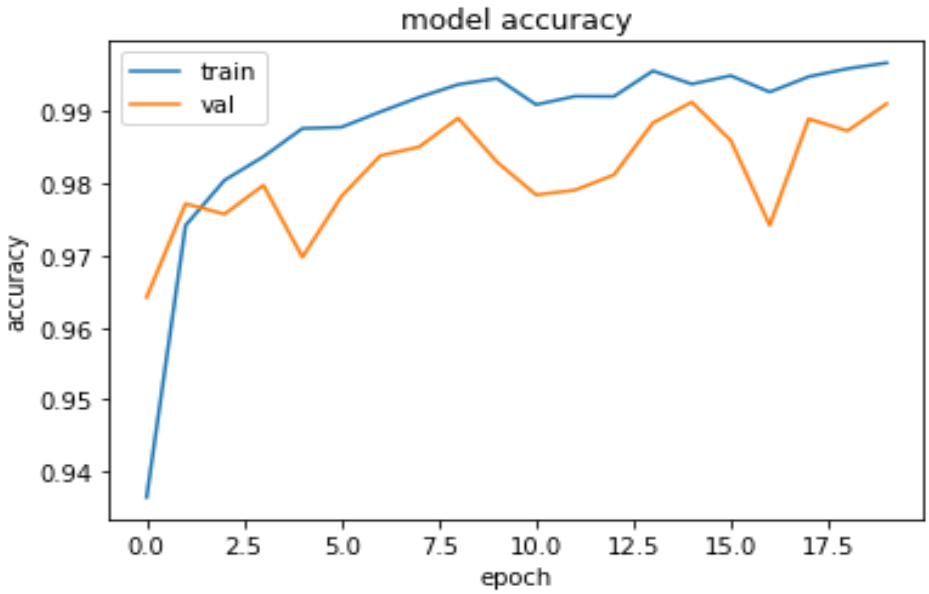

Fig. 3. Accuracy Curve

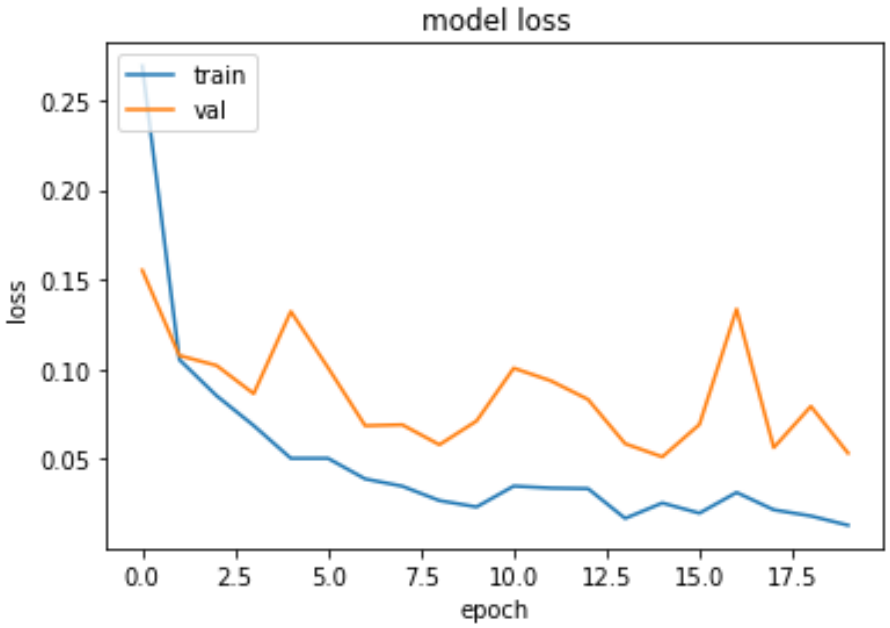

Fig. 4. Loss Error Rate Curve

5. Conclusions

COVID-19 disease had a great impact on the global economy, social life and health. The lack of simple method to identify it was one of the reasons for its spread. Therefore, it was necessary to provide the medical staff with alternative and supportive tools in order to help them to identify the disease through X-ray images in order to make the suitable decisions.

This paper used a modified VGG16 model to recognize COVID-19 from Chest X-ray images. Freezing five layers in our model allowed us to retain the representations learned from ImageNet while adapting the last few layers for COVID detection, which achieved high results due to preventing overfitting. Chest X-rays images from healthy people, patients with pneumonia and COVID-19 were used to create a dataset. These images were split into training and a

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Print ISSN: 2313-190X, Online ISSN: 2520-4912

test dataset. The VGG16 model was trained on 80% of the data set, 15% of this set was used for validation set, and tested on 20%. The proposed model achieved high results compared to previous studies, with an accuracy of 99.13%, a recall of 99% and precision of 98.70%.

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Print ISSN: 2313-190X, Online ISSN: 2520-4912

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Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 50, No. 1, 2024, pp. 133-143
DOI: https://doi.org/10.25195/ijci.v50i1.436
Print ISSN: 2313-190X, Online ISSN: 2520-4912

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