RAPID AUTOMATIC DETECTION OF COVID-19 IN CHEST CT IMAGES USING VGG-16 AND TRANSFER LEARNING

M. Gomroki [1,*] , R. Shah-Hosseini [1], M. Hasanlou [1]

[1] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Tehran, Iran-
(masoomeh.gomroki, rshahosseini, hasanlou)@ut.ac.ir

Commission IV, WG IV/3

KEY WORDS: COVID-19, CT scan, Deep Learning, Automatic Detection, Transfer Learning.

ABSTRACT:

This paper presents a deep learning approach for swift detection of COVID-19 in chest CT scan images in order to facilitate treatment planning and reduce the burden on hospital resources and staff workload. The detection procedure starts with a pre-processing step, which involves noise removal and resizing, and the pre-processed images are fed to VGG16, which is a powerful deep learning network for image classification applications. All algorithms have been implemented in Python and the deep learning network has been implemented in Tesorflow using the Keras library. Using VGG16, we have achieved 99% and 92% accuracy for the training and test data, respectively. Considering the accuracy of the method, it can be used for swift clinical detection of COVID-19, which could be of useful and magnificent help to treatment personnel**.** Also, this method is really helpful for detecting patient and starting treatment as soon as possible and reduces the cost of treatments

1. INTRODUCTION

Severe illness to the human being is caused by a large family of viruses which are named "Coronaviruses". In 2003, The first known severe epidemic is severe acute respiratory syndrome (SARS) occurred, whereas in 2012, the second outbreak of severe illness began in Saudi Arabia with the Middle East Respiratory Syn-drome (MERS) (Punn et al., 2020). Since the discovery of coronaviruses in the 1920s, seven types of these viruses have been identified. In December 2019, an increasing number of then suspected pneumonia cases started to emerge from around the Wuhan seafood market. By January 10, 2020, it was established that these cases are indeed a new type of viral disease originating from Wuhan, China. The world health organization warned about this new type of coronaviruses as an international health emergency disease which would concern by the world , and in February it named the virus "severe acute respiratory syndrome coronavirus 2" (SARS-CoV-2) and called the disease "COVID-19"(Karsaz, 2021).

This virus spread out of China so fast that in less than 3 months there were reported cases of COVID-19 in 164 other countries (Tabrizi and Navkhasi, 2021). In the initial steps, most countries imposed a lockdown to prevent the spreading of this deadly disease. But this is not a totally helpful and practical solution as the whole economy of the particular country goes down. Especially it creates a catastrophic situation for underdeveloped countries in terms of economy (Khan et al., 2021). As of this writing, this virus has infected more than 380 million people, causing more than 5 million deaths worldwide.

Although the majority of countries adopted extensive protective measures to control the spread and there were hopes that the disease might be eradicated with vaccines, the virus has evolved into multiple variants, including the latest one called Omicron, which are still infecting millions of people, causing death and wide-ranging health effects. As official reports show, many

parts of the world have experienced several infection peaks since the start of vaccination in September 2020. The results of these reports for all around the world are illustrated in Figure 1.
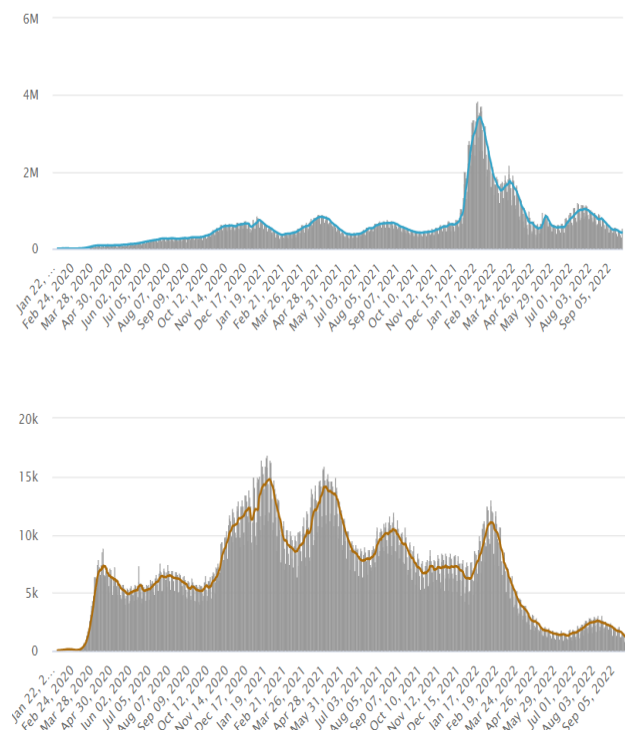

Figure 1. COVID-19 case load (upper graph) and mortality (lower graph) world-wide as of September 5, 2022.

Also, the results of daily new case and death in Iran illustrated in Figure 2.

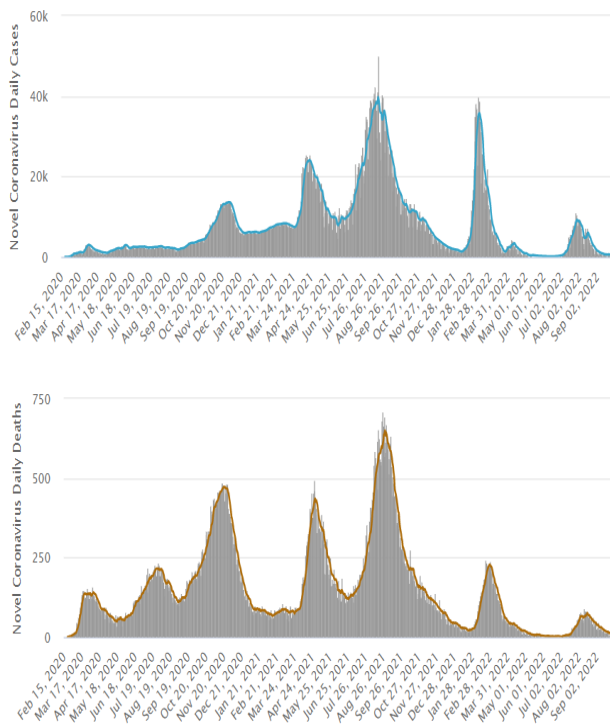---

* Corresponding author

Figure 2. COVID-19 case load (upper graph) and mortality (lower graph) as of September 5, 2022 in Iran

Since COVID-19 is yet to be eradicated, it is still beneficial to develop solutions for timely and accurate detection of infected people. Solutions that might also be effective for similar diseases in the future. Fever, cough, fatigue, headache, and shortness of breath, with emerge in 98%, 76%, 44%, 8% and 3% of patients respectively are the common clinical symptoms of covid 19 (Karsaz, 2021). Serology is employed for detecting antibodies by clinical setups and population surveillance. Detecting every individual affected causes face with limitation of availability of the test kits. Furthermore, these test kits are time consuming, it means that from a few hours to a day takes to produce the results. Besides, most of the time error prone in the current state techniques. Consequently, more reliable and faster way was need exchange with PCR test for purpose of detecting patients (Farooq and Hafeez, 2020). According to the Radiological Society of North America (RSNA), chest x-rays and CT scans, with a 98% success rate, are a more reliable way to diagnose COVID-19 than RT-PCR (Rothan and Byrareddy, 2020).

With regarding the doctors and clinical personnel who are struggling with coronavirus, technologist and researchers are concentrating their efforts to detect the coronavirus infection as soon as possible. In 2019, 755 academic articles which were searched about coronavirus, were published and in first 80 days of 2020 the number of publication about coronavirus reached to 1245. Most of the researchers used deep learning and artificial intelligence methods for detection coronavirus infection from CXR and CT images (Subramanian et al., 2022, p. 19).

Here we provide a brief review of related researches about detection of COVID-19 by employing deep learning methods on chest CT images. In a study by (Karsaz, 2021), he developed a multi-objective self-adaptive differential evolution algorithm for detecting this disease and rating lung involvement using chest CT images. In (Alazab et al., 2020), they analyze the occurrence of COVID-19 distribution across all over world. They proposed

a method which is based on an artificial-intelligence technique based on a deep convolutional neural network (CNN) to detect COVID-19 patients using real-world datasets. Their method examines chest X-ray images to identify such patients, their results achieve 94.8% accuracy. In a study by (Nopour et al., 2021) on the use of data-driven machine learning in COVID-19 detection, they tested and compared a selection of data mining methods, among which J-48 algorithm managed to achieve 85% accuracy.

(Tabrizi and Navkhasi, 2021) used a combination of deep learning and water wave optimization algorithm for COVID-19 detection and reported that the method offered 98% accuracy. In a study by (Narin et al., 2021), where the ResNet50 network was used to detect COVID-19 in CT scans, they reported achieving 98% accuracy with this method. In another study by applying deep learning algorithms such as VGG16, AlexNet, VGG19, ResNet-18, GoogLeNet, ResNet-101, ResNet-50, Inception-ResNet-v2, DenseNet-201, Inception-v3, and XceptionNet to chest X-ray images, (Sethy and Behera, 2020) extracted some features to indicate that if they are infected or healthy using support vector machine method (SVM). Their models are implemented two datasets. The first one indicates X-ray images of 25 infected and 25 non-infected patients, the second one includes 133 chest X-ray SARS, MERS and ARDS patients and 133 chest X-ray non-patients. Their final result shows that ResNet50 and SVM can reach the best result in separating feature extraction and achieved 95.38% accuracy. In addition, (Mahdy et al., 2020) proposed a classification method which is based on multi-level thresholding and a SVM for detecting COVID-19 purpose in lung X-ray images which have the resolution of 512×512 pixels. Their system was tested on 40 contrast-enhanced lung X-ray images that included 15 healthy and 25 COVID-19-infected regions. Their classification system achieved a sensitivity, specificity and accuracy of 95.76%, 99.7% and 97.48%, respectively.

The COVID-19 detection performance of convolutional neural networks with seven different architectures is compared by (Hemdan et al., 2020), reporting that the best performance belonged to VGG16 and Densenet networks with F1-score of 91% and 89%, respectively. A convolutional network with VGG16 architecture and a long short-term memory (LSTM) network is combined in (Islam et al., 2020) for COVID-19 detection, achieving 99% accuracy.

An automatic identification method is implemented using deep learning algorithms by (Gozes et al., 2020) on covid 19 patients. This method is applied to CT scans to examine the burden quantification of disease and they used a dataset consist of 157 CT scans of patients from China and USA.

In another study ten different CNN models including: SqueezeNet, AlexNet, VGG-19, VGG-16, GoogleNet, MobileNet-V2, ResNet-101, ResNet-18, ResNet-50 and Xception are used by (Ardakani et al., 2020) for detecting covid 19 in CT images. They implement their proposed methods on 1020 covid 19 and non-covid 19 CT images. The ratio between training and validation set is 80% and 20% respectively. Among their 10 proposed methods, ResNet101 and Xception have the best performance. Exprimental result showed that the ResNet-101 model reached accuracy of 99.51%, sensitiv-ity of 100%, AUC of 99.4%, and specificity of 99.02%. The other network, Xception obtained the accuracy of 99.02%, sensitivity 98.04%, AUC of 87.3% , and specificity of 100%.

By applying a powerful pre-trained model UNet++ to a collection of high resolution CT images for covid 19 patients, (Chen et al., 2020) introduced a deep learning-based scheme to detect infected cases. First of all, UNet++ segmentation indicated defected regions in CT images. A database included 46096 CT images consist of 51 covid 19 infected patients and 55 patients with other disease are gathered from the hospital. 10741 low images were eliminated by filtering among data set so that the remaining images were partitioned into training and testing sets. The results reached sensitivity, specificity, accuracy, precision and negative predictive value (NPV) of 94.34%, 99.16%, 98.85%, 88.37% and 99.61%, respectively. Another scheme is introduced by (Cifci, 2020) for early diagnosis of coronavirus affection, this scheme combined two pre-trained models of Alexnet and Inception-V4 (which are commonly applied to medical images analysis) with deep transfer learning, for this study the CT images of patients are investigated. The data which are used in this study is 5800 CT images which are retrieved from a public repository. 80% of thoses samples are used for training data while remain samples are considered as testing data. Experimental results showed that AlexNet had a better performance in comparison with Inception-V4. AlexNet got overall accuracy, sensitivity, specificity of 94.74%, 87.37% and 87.45%, respectively.

Given the limited size of data banks and limited number of images available for this virus, (Waheed et al., 2020) used an auxiliary Generative Adversarial Network (GAN) alongside VGG16 to enhance the performance of the deep learning network.The detection of covid 19 using GAN and pre-trained models of CNN which are used transfer learning was bringed forward by (Loey et al., 2020) as an inventive method. In the proposed system the pre-trained models of AlexNet, GoogleNet and ResNet18 are utilized. As we known GANs is implemented to generate more samples for more reliable detetion of various because the number of covid19 samples is small. A dataset including 307 X-ray images are supposed consist of 4 classes as covid 19, normal, pneumonia and pneumonia. The system examined on 3 different scenarios of the dataset depending on the consideration of class level. Assuming 4 classes, GoogleNet achieved the maximum accuracy of 85.2% and 100% respectively by assuming three and two classes.

In a study by (Jain et al., 2021), where they compared the performance of three deep learning architectures namely ResNet, Xception, and Inception in differentiating COVID-19 cases from healthy individuals, Xception offered the best performance with up to 98% accuracy.A COVID-19 detection model called Covid-RENet is developed by (Cohen et al., 2020, p. 19), where edge and region feature extraction is done by a convolutional neural network and then a support vector machine is used to enhance the classification of lung CT images. In a study by (Li et al., 2020), they used a deep learning model to differentiate lung images of people with COVID-19 from those of healthy individuals.

Recently developed systems which generally reviewed by (Islam et al., 2021) are based on deep learning techniques in which different medical images are used such as CT and X-ray images. They particularly talk through the systems developed for covid 19 diagnosis using deep learning techniques and makes insights about popular datasets used to train these networks.
(Subramanian et al., 2022, p. 19) proposed a literature review of the deep learning methods that are currently available and using for detection of coronavirus infection in lung images. All methods, public datasets, datasets that are used by each method

and evaluation metrics are illustrated in their paper to help future researchers. Besides, the evaluation metrics that are used by the researchers are comprehensively compared.

From this review of the research literature, one can conclude that deep learning methods are indeed effective in early detection of COVID-19 and CT scan images can indeed serve as the main means of this detection. Since deep learning networks tend to take a lot of time to accomplish their task, in this study, the transfer learning method has been used to speed up the network process so that COVID-19 cases can be differentiated from healthy cases in much shorter times. Furthermore, the proposed method involves using much less training data than a network would normally require, which can be a great advantage given the limited access to chest CT data banks for COVID-19. Considering the multitude of reports in the literature on the excellent image classification performance of VGG16, this deep learning network has been chosen for modification with transfer learning. In addition to accelerating the process of differentiating COVID-19 and healthy instances in chest CT images, which can benefit treatment measures, the proposed method could be a step toward the detection of similar conditions in the future. Furthermore, the proposed method can take in new training data and use them to enhance network performance, which means the network can always be updated with new data and will have an online training capability

2. METHOD

In (Asefi and Safaie, 2020, p. 19) it has been showed that the comparison of chest CT images between patients with positive RT-PCR results and patients with the negative one shows a high correlation about 97%.. Sixty to 93% of patients had positive chest CT findings for COVID-19 before or at the same time as the initial positive RT-PCR results. On the other hand, typical CT scan findings were found in more than 70% of patients with negative RT-PCR tests, which could be due to overlap of CT imaging features of COVID-19 and other viral pneumonias or the high false-negative rate of the RT-PCR tests. Analysis of the patient therapeutic information implies that the rate of 89% pooled accuracy for RT-PCR is comparable with the rate of 94% of pooled sensitivity of chest CT images in detection of COVID-19. However, the pooled specificity of those images had rate of 37% for that purpose

In this study, chest CT images of healthy people and people with COVID-19 were used for automatic COVID-19 detection. This dataset includes 25 images chest CT scan of normal and 25 images of covid people. An example of these images is shown in Figure 3.

The flowchart of the method is provided in Figure 4. As this flowchart shows, the method starts with a pre-processing step, which includes noise removal and resizing, to prepare the images for use in the network. This is followed by the main processing step, which involves feeding the pre-processed data to a VGG16 network that has been previously configured for another problem but is partially modified using the transfer learning approach, transfer learning not only improves the ability of our network for detecting covid from normal images but also solve the problem of small dataset, as mentioned before the dataset only include 25 covid images and 25 normal images so we have to use the method which compensates the small dataset problem. After processing CT images, this network generates a classification-type output, which separates healthy instances from COVID-19 instances.
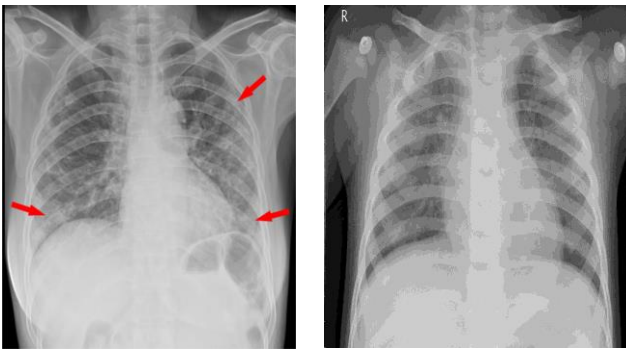
Figure 3. Chest CT image of a healthy person (right), Chest CT image of a person with COVID-19 with red arrows showing involved areas (left).
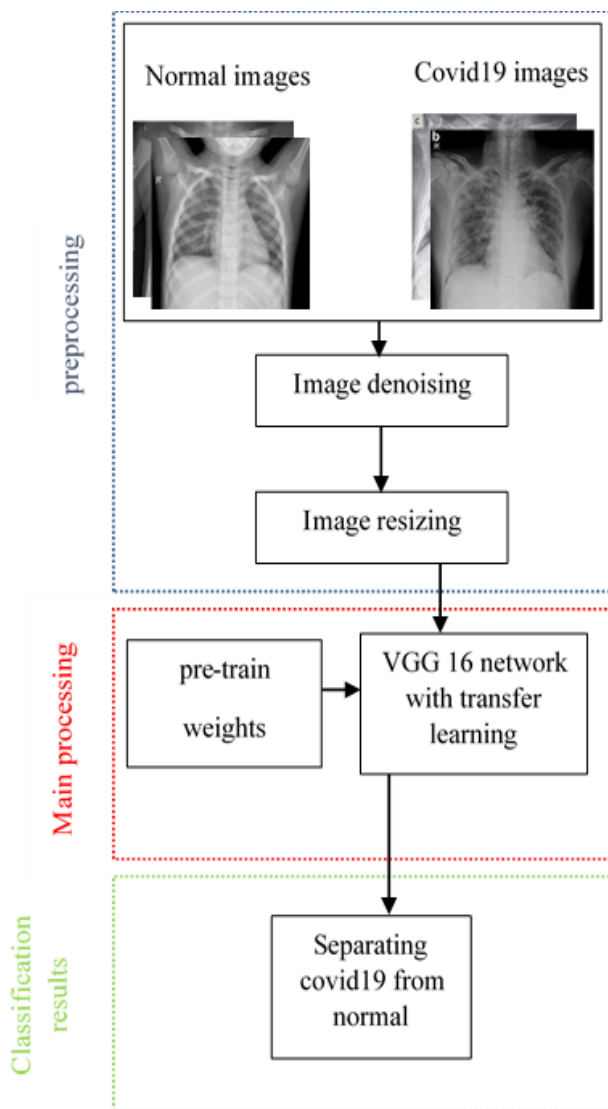
with stride 2, which in addition to sampling, is also tasked with reducing the feature dimension by half. The second block is comprised of two other convolutional layers with 128-channel 3×3 filters and a 2×2 maxpooling layer with stride 2. The third block consists of three convolutional layers with 256-channel 3×3 filters and a maxpooling layer. The following two blocks have three convolutional layers with 512-channel 3×3 filters and a maxpooling layer. In the end, the features are turned into a feature vector and given to a block of fully-connected layers. This block consists of three fully-connected layers, of which two are of size 4096 and the last one is of size 1000 (corresponding to the number of classes in the Imagenet challenge), all using the Relu activation function. Figure 5 illustrates the architecture of the described VGG16 network.
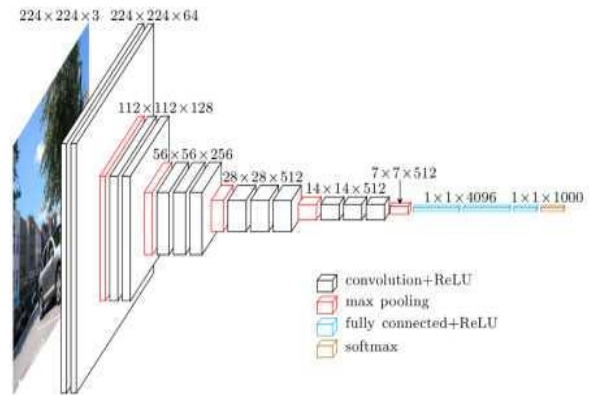

Figure 5. VGG16 network architecture.

We can add one more layer or retrain the last layer to extract the main features of our image. We can also give the weight of VGG16 and train again, instead of using random weight (Fine Tuning). Figure 6 shows the architecture of VGG16 which is used for transfer learning. In this architecture three last dense layer replaced for new problem.
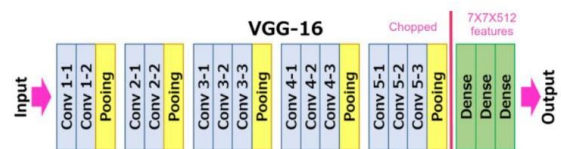

Figure 6. VGG16 network architecture with transfer learning

In this study, we have used this trained VGG16 network as is up to the feature vector generation step, but have replaced the block of fully-connected layers with another stack of layers more suitable for COVID-19 data. In other words, we have used the transfer learning method, whereby models trained with large datasets can be reused with the trained weights to build a model for another problem. In this study, the transfer learning process involved freezing the original VGG16 network with pre-trained weights, adding two dense layers suitable for the data type to the network, and then training the model. One of the added dense layers is of size 256 with Relu activation function and the other is of size 1 with Sigmoid activation function. These layers have been placed at the end of the network (in place of fully-connected layers) for the final classification of COVID-19 and healthy instances. This network is able to accurately

Figure 4. Flowchart of the proposed method.

The study uses the VGG16 network, which was first developed by (Simonyan and Zisserman, 2014) for classifying 16 million images in 1000 classes for the Imagenet challenge. The VGG network is available in two different architectures called VGG16 and VGG19. VGG16 has 16 convolutional layers. The first block of layers consists of two serial convolutional layers with 64-channel 3×3 filters followed by a 2×2 maxpooling layer

differentiate COVID-19 instances from healthy instances at a very high rate. The summary of this model is illustrated in Table 1.

Layer (type)	Output Shape	Param #
vgg16 (Model)	(None,7,7,512)	14714688
max_pooling2d_2(MaxPooling2)	(None,1,1,512)	0
flatten_2 (Flatten)	(None,512)	0
dense_4 (Dense)	(None,64)	32832
dense_5 (Dense)	(None,2)	130
Total params: 14,747,650		
Trainable params: 32,962		
Non-trainable params: 14,714,688		

Table 1. The summary of this model.

3. RESULTS AND DISCUSSION

As shown in the diagrams of Figure 7, the network has reached an appropriate level of convergence after 40 epochs, achieving 99% accuracy for the training data and 92% accuracy for the test data.
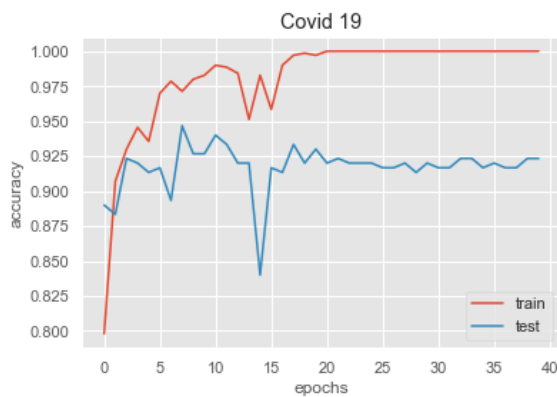

Figure 7. Accuracy for the training and test data.

After 40 epochs the model reached 0.7% and 30% loss foe training and test data, respectively. The result of loss function is shown in Figure 8.
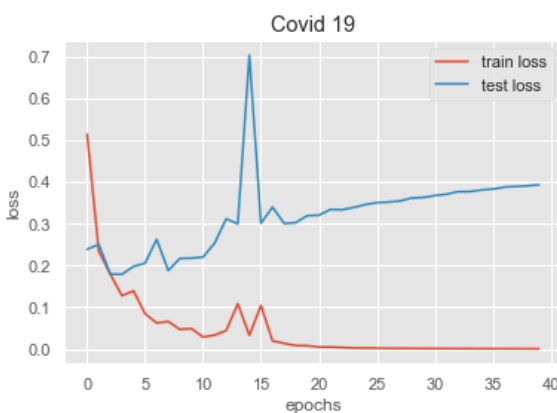

Figure 8. Loss for the training and test data.

Also, the confusion matrix which is the result of comparison between normal and covid cases is shown in Figure 9.
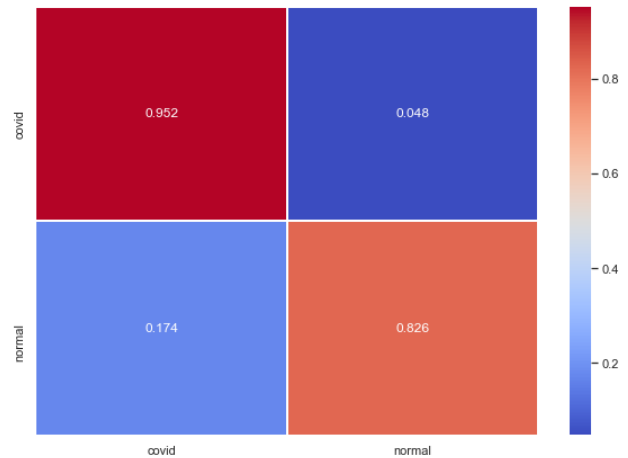

Figure 9. Confusion matrix.

From the plotted diagrams, we can conclude that the method and specifically the transfer learning mechanism it utilizes allows for fast differentiation of images belonging to patients from those belonging to healthy individuals. Using categorical cross entropy loss function and a batch size of 4 for classification, the outputs converged after 40 epochs, showing no significant change thereafter.

The obtained results demonstrate the ability of the VGG16 network modified with transfer learning to rapidly differentiate healthy and COVID-19 instances at acceptable accuracy levels.

REFERENCES

Alazab, M., Awajan, A., Mesleh, A., Abraham, A., Jatana, V., Alhyari, S., 2020. COVID-19 prediction and detection using deep learning. International Journal of Computer Information Systems and Industrial Management Applications 12, 168–181.

Ardakani, A.A., Kanafi, A.R., Acharya, U.R., Khadem, N., Mohammadi, A., 2020. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. Computers in biology and medicine 121, 103795.

Asefi, H., Safaie, A., 2020. The role of chest CT scan in diagnosis of COVID-19. Frontiers in Emergency Medicine 4, e64–e64.

Chen, J., Wu, L., Zhang, J., Zhang, L., Gong, D., Zhao, Y., Chen, Q., Huang, S., Yang, M., Yang, X., 2020. Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography. Scientific reports 10, 1–11.

Cifci, M.A., 2020. Deep learning model for diagnosis of corona virus disease from CT images. Int. J. Sci. Eng. Res 11, 273–278.

Cohen, J.P., Morrison, P., Dao, L., 2020. COVID-19 image data collection. arXiv preprint arXiv:2003.11597.

Farooq, M., Hafeez, A., 2020. Covid-resnet: A deep learning framework for screening of covid19 from radiographs. arXiv preprint arXiv:2003.14395.

Gozes, O., Frid-Adar, M., Greenspan, H., Browning, P.D., Zhang, H., Ji, W., Bernheim, A., Siegel, E., 2020. Rapid ai development cycle for the coronavirus (covid-19) pandemic: Initial results for automated detection & patient monitoring using deep learning ct image analysis. arXiv preprint arXiv:2003.05037.

Hemdan, E.E.-D., Shouman, M.A., Karar, M.E., 2020. Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images. arXiv preprint arXiv:2003.11055.

Islam, M.M., Karray, F., Alhajj, R., Zeng, J., 2021. A review on deep learning techniques for the diagnosis of novel coronavirus (COVID-19). Ieee Access 9, 30551–30572.

Islam, M.Z., Islam, M.M., Asraf, A., 2020. A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images. Informatics in medicine unlocked 20, 100412.

Jain, R., Gupta, M., Taneja, S., Hemanth, D.J., 2021. Deep learning based detection and analysis of COVID-19 on chest X-ray images. Applied Intelligence 51, 1690–1700.

Karsaz, A., 2021. Evaluation of Lung Involvement in Patients with Coronavirus Disease from Chest CT Images Using Multi-Objective Self-Adaptive Differential Evolution Approach. Journal of Control 14, 1–14.

Khan, M.Z., Khan, M.U.G., Saba, T., Razzak, I., Rehman, A., Bahaj, S.A., 2021. Hot-Spot zone detection to tackle COVID19 spread by fusing the traditional machine learning and deep learning approaches of computer vision. Ieee Access 9, 100040–100049.

Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., Bai, J., Lu, Y., Fang, Z., Song, Q., 2020. Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. Radiology.

Loey, M., Smarandache, F., M. Khalifa, N.E., 2020. Within the lack of chest COVID-19 X-ray dataset: a novel detection model based on GAN and deep transfer learning. Symmetry 12, 651.

Mahdy, L.N., Ezzat, K.A., Elmousalami, H.H., Ella, H.A., Hassanien, A.E., 2020. Automatic x-ray covid-19 lung image classification system based on multi-level thresholding and support vector machine. MedRxiv.

Narin, A., Kaya, C., Pamuk, Z., 2021. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. Pattern Analysis and Applications 24, 1207–1220.

Nopour, R., Shanbehzadeh, M., Kazemi-Arpanahi, H., 2021. Proposing an effective technological solution for the early diagnosis of COVID-19: a data-driven machine learning study. Journal of Modern Medical Information Sciences 7, 68–78.

Punn, N.S., Sonbhadra, S.K., Agarwal, S., 2020. COVID-19 epidemic analysis using machine learning and deep learning algorithms. MedRxiv.

Rothan, H.A., Byrareddy, S.N., 2020. The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak. Journal of autoimmunity 109, 102433.

Sethy, P.K., Behera, S.K., 2020. Detection of coronavirus disease (covid-19) based on deep features.

Simonyan, K., Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

Subramanian, N., Elharrouss, O., Al-Maadeed, S., Chowdhury, M., 2022. A review of deep learning-based detection methods for COVID-19. Computers in Biology and Medicine 105233.

Tabrizi, N., Navkhasi, S., 2021. Automatic and Accurate Diagnosis of COVID-19 by Chest CT scan Images Using Deep Learning Method. Journal of Marine Medicine 3, 41–48.

Waheed, A., Goyal, M., Gupta, D., Khanna, A., Al-Turjman, F., Pinheiro, P.R., 2020. Covidgan: data augmentation using auxiliary classifier gan for improved covid-19 detection. Ieee Access 8, 91916–91923.