Solving A Problem of COVID-19 Classification Using Improved VGG Deep Learning Model Updating

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Abstract. Computer vision is an important field in computer science. There are many technologies in the field of computer vision in order to develop basic solutions to many problems. One of these problems that computer vision techniques work to solve is the classification and recognition of medical images of all kinds. For example, the classification of medical images related to the disease of the century, which is covid 19. Deep learning is responsible for developing computer vision. It is a subset of artificial intelligence (AI). The aim of this study is to classify medical images using deep learning algorithms in the fastest time and with high accuracy. Several deep learning models improve image classification. The best of these models has been used in this manuscript database where the database comes from the Kaggle site with the name Chest X-Ray Images (Pneumonia). The result was obtained using the model VGG16 that modification by the operative (new) layers where the accuracy was 99.35%. These results will be helpful for clinicians in classifying medical images with high accuracy and speed.

Keywords: Image Classification, Medical Image, Deep Learning, Models, Operative Layers, Covid 19.

1- Introduction

Coronavirus disease (Covid-19) is a pandemic illness caused by the SARS-CoV-2. Coronaviruses are named because of their look. The word corona means crown. Name comes from the outer layers of the virus are covered with spike proteins that surround them like a crown. Coronavirus is a viral disease that appeared in the Chinese city of Wuhan. Covid 19 has spread quickly over the world [1]. The following Fig.1 shows a common class of the covid 19 family.

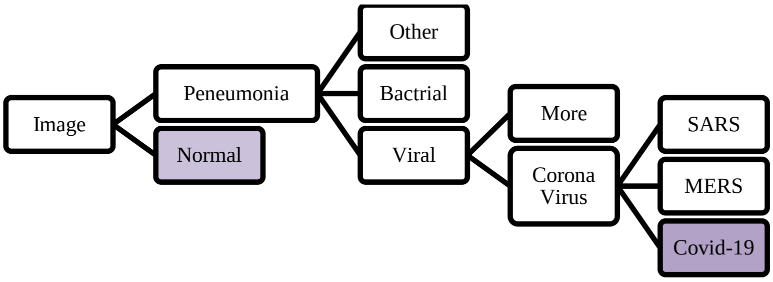


Fig. 1. Family tree of covid -19.

Covid 19 disease has many symptoms that indicate infection. Fewer symptoms of covid 19 are sore throat, a headache, aches, diarrhea, a rash on skin, and irritated eyes. Most common symptoms are fever, cough, tiredness, and loss of taste or smell. Serious symptoms are difficulty breathing or shortness of breath loss of speech or mobility, and also chest pain. Most researchers are aware that the coronavirus spreads through droplets when an infected human breathes and speaks. Covid-19 tests have two methods the first one is the PCR test and the second is the antigen test. Polymerase chain reaction (PCR) tests for showing actual virus genetic material as it degrades. The antigen test discovers bits of proteins on the surface of the virus called antigens. The antigen test is usually rapid but less sensory than the PCR test.

When a person is infected, doctors need to know what is going on inside the body, so they ask the affected person to have a diagnostic imaging test. There are several types of imaging tests. Three common types of imaging are X-rays, computed tomography (CT), and magnetic resonance imaging (MRI). X-rays are used for diagnosing and assessing diseases. It only takes a few minutes. In this study, x-rays were used because they are cheap, fast, and available in all hospitals. It is also advantageous that there are a huge number of images available for this disease. Low-quality or unreadable chest x-ray images remove. In order to avoid misdiagnosis, the data was trained on AI models.

In 1950, the problem of classifying images appeared. Several methods are used to solve this problem such as Support Vector Machine (SVM), Nearest Neighbor Algorithm (KNN) and Artificial Neural Network (ANN). There are many areas in which deep learning is used to obtain satisfactory and good results, for example in the field of engineering, medicine, agriculture, industry, space research, etc. In engineering research, for example, Alshboul, et al. used a genetic algorithm and Artificial Neural to minimize the time and cost objective for earthmoving equipment [2] and also predicted the costs of a green building via machine learning approaches [3]. In South Korea, digital images of bridge surfaces are detected by deep learning [4]. In medicine field, classification of biomedical images is being investigated by artificial intelligence methods [5]. Mohapatra showed how deep convolutional neural networks use in medical image processing [6].

In recent years, deep learning technology has been used for analyzing medical images in various fields, and it shows excellent performance in various applications such as segmentation and classification. The classical method of image segmentation is based on edge detection filters and several mathematical algorithms. Deep Learning involves taking large volumes of structured or unstructured data and using complex algorithms to train neural networks. It performs complex operations to extract hidden patterns and features (for example, distinguishing the image of a normal from that of an abnormal). The reasons for choosing DL in medical image classification are access to the high structure of data, availability of performing and advanced algorithms. A deep learning (DL) algorithm can be used to automatically diagnose covid 19.

The aim of this study is to classify medical images using VGG updating deep learning algorithms in the fastest time and with high accuracy (the best compromise between precision and speed) [7]. We tested the network with different training datasets extracted from different feature images to obtain generalizable results. We finally implement a pipeline to model to start from the output of the classification and compare it with the previous approach based solely on Convolutional Neural Network (CNN) techniques.

Recently, many researchers have used Convolutional Neural Network (CNN), which is an important type of Artificial Neural Network (ANN). A convolutional neural network has many advantages. For example, the simplicity of this network is by repeatedly applying a filter wrap operation on the entire input elements. It improves performance significantly, because it will lead to a large number of connections but with common weights to parts of the image, and finally reduces the complex memory and preservation compared to other types. The subset of deep learning is the convolutional neural network (CNN). CNN plays an important role in different areas of medical image classification [8].

There are many types of convolutional neural networks including LeNet, Alex Net, ResNet, Google Net/Inception, MobileNetV1, and VGG16. Image classification generally consists of two steps. The first step is called the convolutional rule used to extract the features. The second phase is called a classifier trained to classify the input image to get the output result. Both the above steps are used in our model. Implementing the image classification model using the Visual Geometry Group (VGG 16) model and modifying it in the last layer, gave the best classification results. The purpose of the model in this paper is to perform binary classification of covid19 image data using New VGG deep learning [9].

Improved VGG deep learning is a hybrid between deep learning (DL) and Augmented Reality (AR) based solutions for assisted radical, to improve medical work [10]. When deep operative learning (Improved VGG) is implemented, for example, the automatic system will align a virtual image model of a patient with its endoscopic image, to assist doctors during the diagnosis. Reducing time and working with high efficiency are among the reasons that led to the tendency to use the proposed modern method of updating VGG deep learning. Fig. 2 shows a general diagram of the proposed new method of the neural network depend on new layers.

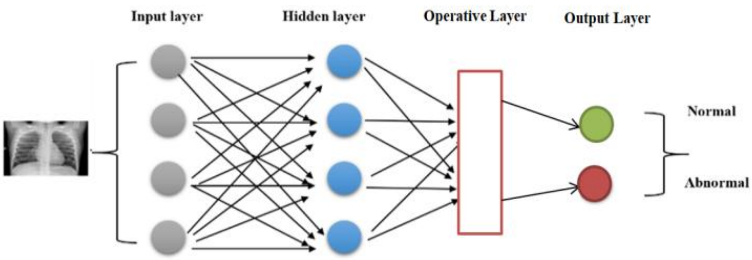


Fig. 2. *General diagram of new deep learning*

2-Related Work

In the past few years, humanity has faced many challenges such as the spread of diseases all over the world. This, of course, led many researchers in all fields to study and analyze these difficulties. One such difficulty is the coronavirus pandemic. In the field of computer science, many methods have been used to classify medical images, specifically corona images [11]. Combining computer vision with the concept of deep learning is one way to give practical results. In fact, many researchers have used DL models to classify coronavirus images.

Nishio M et al. summary of covid-19 DL models [12]. Singh, Mukul, et al. [13] investigates the potential of transfer learning–based models for automatically diagnosing diseases like covid-19. Shi, Feng, et al. used Large-scale screening to distinguish between covid-19 and community-acquired pneumonia using infection size-aware classification [14]. Bai, Harrison X., et al. [15] establish and evaluate an artificial intelligence (AI) system in differentiating covid-19 and assess radiologist performance without and with AI assistance. Singh, Dilbag, Vijay Kumar, and Manjit Kaur [16] used multi-objective differential evolution–based convolutional neural networks for the classification of covid-19 patients from chest CT images. Özkaya, Umut, Şaban Öztürk, and Mucahid Barstugan [17] investigated deep features fusion and ranking techniques for Coronavirus (covid-19) classification. Mukherjee, Himadri, et al. [18] detected covid-19- using a light-weight CNN-tailored shallow architecture. Saberi et al. 's innovative approach to discarding redundant features from the set of original features is called Dual Regularized Unsupervised Feature Selection [19].

Laddha, Saloni, et al. review various publications and research articles published from March 2020 onwards about image classification [20]. Priya Aggarwala Narendra and Kumar Mishra el. summarize and review a number of significant research publications on the DL-based classification of covid-19 through CXR and CT images [21]. Micheal Olaolu and Roseline Oluwaseun, el al. apply a machine learning method for the prediction of covid-19 incidence, using KPCA-SVM [22]. Muhammad, L. J., et al. supervised deep learning algorithm obtained strong covid-19 detection performance [23]. Based on the richer feature representation, Yan, Rui, et al. proposed a method for breast cancer image classification using a convolutional and recurrent deep neural network [24]. Murata, Makoto, et al. aims to develop a completely automated system for the diagnosis of panoramic images by creating more accurate deep-learning models [25]. Based on previous studies in computer science and previous research, a new method for classifying images based on updating VGG deep learning has been developed. The main motive of this study is to assist clinicians in diagnosing and detecting patients in a correct, safe and rapid manner. Finally, medical imaging models have a major role in spontaneous diagnosis and classification.

3- Proposed Methodology

The proposed approach was used to classify medical images using deep learning. In this section, we propose the architecture and detailed learning for the CNN model due to medical image classification. In addition, we describe the transferring learning approach. This study aims to perform the automatic classification of medical images based on the updating VGG deep learning model and optimization through fine-tuning and transfer learning. Fig. 3 illustrates the framework of the proposed model.

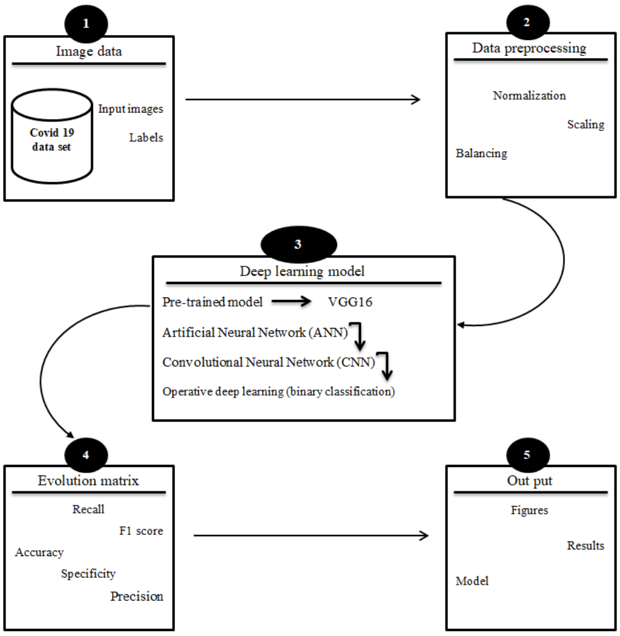


Fig. 3. *The proposed framework of the updating VGG deep learning pipeline.*

In 2021, Khasawneh, N., et al. published a research paper of scientific value [26]. Where the authors used VGG and MobileNets models to classify covid images, achieving an accuracy of more than 98%. As an extension of this work, we made a mathematical framework and developed mathematical equations to employ the models used. We used data of the same type (x-ray), but different in number and composition. Under the proposed model, an accuracy of more than 99% has been achieved. We modified the (VGG) model in a mathematical framework using transfer learning. DL methods have been successful in classifying images, the details of which will be discussed next [27].

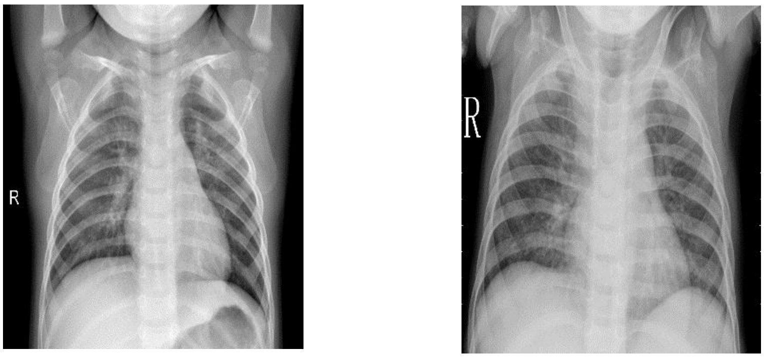
3.1 Data Preparing

This step involves converting the raw data images to an appropriate format. Some images were sent to training after we labeled them. Table 1 presents this data. The model uses the covid 19 dataset [28].

Table 1. Datasets Information.

Data Type	Training data	Testing data
Normal	1341	234
Abnormal	3875	390

The basic findings of new studies suggest that these lung images show patchy or diffuse reticular–nodular opacities and consolidation, with basal, peripheral, and bilateral predominance [29]. More than 5,000 images were used in the proposed new model. Fig. 4 shows a sample of images that will be used in the CNN model. The normal image has clear lungs without any areas of an abnormality like in image (a). The abnormal image has a more diffuse ‘‘interstitial’’ pattern in both lungs like in the image (b).



(a) (b)

Fig. 4. *Samples of data set: (a) normal image; (b) abnormal image.*

3.2 Data preprocessing

It largely involves normalization, resizing, feature extraction and transformation. We normalize and resize our dataset images. The meaning of normalization is that the pixel values in magicians are scaled before they are implemented in deep learning. For example, the standards score normalization (z-normalization) can also be represented as:

$$x_i' = \frac{x_i - \mu}{\sigma} \quad (1)$$

Where x_i', x_i, μ and σ are output pixel value, Input pixel value, mean and standard deviation respectively. Where the mean equation is

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (2)$$

and the standard deviation equation is,

$$\sigma = \frac{1}{n}\sum_{i=1}^{n} x_i - \mu \quad (3)$$

To normalize our data, each pixel of image values divides by 255 to rescale pixel values into the 0-1 range and reshapes them into 200×200 square photos. All the images are loaded, reshaped, and stored as a single NumPy array.

Image resizing is the operation of changing the width and height of the image, preferably maintaining the aspect ratio to prevent image compression or destroy the image to be suitable for use in our algorithm. The image data source has different sizes, so we had to resize it before being used in most of the neural network models. To remove the noise in the images, different image filtering techniques are used. To remove even a small quantity of noise, Gaussian blurring is used (filter 3x3)[30].

3.3 Deep learning model

Artificial Neural Network (ANN) composition is more similar to the human brain structure. The main configuration of the Artificial Neural Network consists of three layers, which are in order an input, a hidden, and an output layer. In the case of not using the hidden layer, the network is called a single model, but in the case of using three layers, it is called multiple models. It must be taken into account that the hidden layer may contain several other layers.

In the hidden layers, the most complex operations of artificial intelligence networks are carried out through the use of activation functions (AFs) [31]. The main aim of using functions is to aid learning and add non-linearity to the neural network The choice of the activation function depends on the type of neural network used and the purpose to be achieved in the output layer [32]. For example, the rectified linear unit (ReLU) is a famous activation function good at Convolutional Neural Networks (CNN) but Tanh is an activation function good at Recurrent Neural Networks [33]. Fig. 5 shows us the representation of ReLU. The common guideline is hidden layer uses the same activation function. There are rules for choosing the activation function such as in binary Classification, Sigmoid/Logistic is a good activation function.

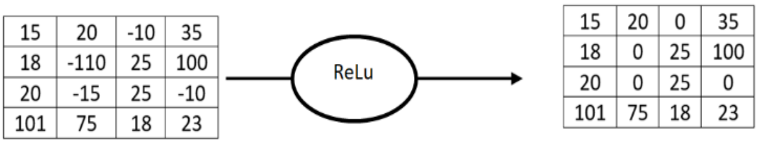


Fig. 5. *ReLu Activation function*.

An important kind of artificial neural network is a convolutional neural network. CNN is used to express a DL that is able to solve many problems in the computer vision field like the classification of medical image. Convolutional layer, the pooling layer, and the fully connected layer are the three most important layers that make up a convolutional neural network (CNN). The next part will explain the most important CNN concepts used in the classification process.

Convolutional layer: The convolution process uses the image input to the filter and passes to the image pixels to extract the features to create the output function as a feature map for this image, thus reducing the storage space in which each image is stored. Another convolution layer can follow the initial convolution layer so that later layers can see the pixels within the receptive fields of prior layers [34]. Convolution operations can generally be written in the form below:

$$y(t) = (x * w) \tag{4}$$

The equation $y(t)$ gives the results of a feature map and x indicates input but w is the filter. In two dimensions, t was replaced with arguments i and j. Therefore, the convolution operations with can write as follows:

$$y(i,j) = (k * I)(I,j) = \sum_n \sum_m (i-m)(j-n)\, k(m,n) \tag{5}$$

The convolutional layer is the basic mason block. There are three hyper parameters: depth, stride, and setting zero padding. Let us see these important parameters.

Depth (K)*:* More than a number of neurons can be assigned to the same input region. K is the depth of the activation map.

Stride (S)*:* Normally use stride step size value is 1 or 2. A smaller stride will lead to overlapping receptive filed and larger output volumes and vice versa [35]. For example, when $S = 1$ this means the kernel or filter slides one pixel at a time from left to right and also top to bottom.

Zero padding (P)*:* We need to cover the image borders to maintain the image's original size. Zero padding using the size of the output sizes matches our input size. The convolutional layer accepts input volume size $[W_i * H_i * D_i]$ where $W_i = input\ width$, $H_i = input\ height$ and $D_i = input\ depth$.

Finally, to obtain the output of the convolutional layer is $[W_O * H_O * D_O]$ where:

$$W_O = output\ width = \frac{W_i - F + 2*P}{S} + 1 \tag{6}$$

$$H_O = output\ height = \frac{H_i - F + 2*P}{S} + 1 \tag{7}$$

$$D_O = output\ depth = K$$

From the previous equations, we use four important parameters: number of filters (K), stride (S), the amount of zero padding (P) and receptive field size (F).

Pooling layer: CNN has an important building block called the pooling layer. It is executed after each convolutional layer. The pooling operation sweeps a filter across the entire input, but this filter does not have any weights. The aggregation process involves moving a $2D$ filter over each channel in the feature map as it summarizes the features within the area covered by the filter. Pooling layers reduce the number of parameters in the input. The pooling layer accepts input volume size $[W_i * H_i * D_i]$. To obtain the output of the layer is $[W_O * H_O * D_O]$ where:

$$W_O = output\ width = \frac{W_i - F}{S} + 1 \tag{8}$$

$$H_O = output\ height = \frac{H_i - F}{S} + 1 \tag{9}$$

$$D_O = output\ depth = D_i$$

The pooling layer has main two types which are max and average pooling. Equation (10) shows average pooling which calculates the average value of pixels when the filter moves.

$$y_{ij} = Average(\, x_{ij}) \tag{10}$$

Equation (11) offers max pooling which takes the pixel with the maximum value when the filter changes to another place.

$$y_{ij} = \max(\, x_{ij}) \tag{11}$$

The following Fig. 6 shows how the pooling layers perform.

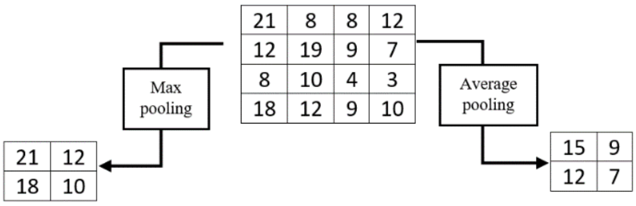


Fig. 6. Representation of max and average pooling 2 x 2 with stride 2

Fully connected layer: The fully connected (FC) layer executes the mission of classification founded on the features extracted through the past layers. While convolutional and pooling layers tend to utilize ReLU, FC layers commonly leverage a softmax activation function to classify inputs, producing a probability from 0 to 1[36]. A fully connected layer uses a weight matrix and then adds a bias vector. The fully connected layers come after the convolution layer. All neurons in a fully connected layer link together. We can divide the entire neural network classification into two parts: feature extraction (extracting features from the data to make the classification) and classification (classifying the data into various classes).

It should be borne in mind; the batch normalization is used to standardize the inputs to the convolutions by calculating the mean and standard deviation across the minimum batch; dropout can also help reduce over fitting[37].

Relying on the pre-trained CNN model, VGG16, transfer learning is used as feature extraction [38]. When we use deep learning models, there are some problems that we face like overfitting, the gap of public datasets and the system that requires a lot of training and testing which wastes time and money. One of the best solutions is the transfer learning approach. There are two approaches used in transfer learning that solve these problems, the first is fine-tuning, and the second is feature extraction. Fig. 7 shows an overview of transfer learning.

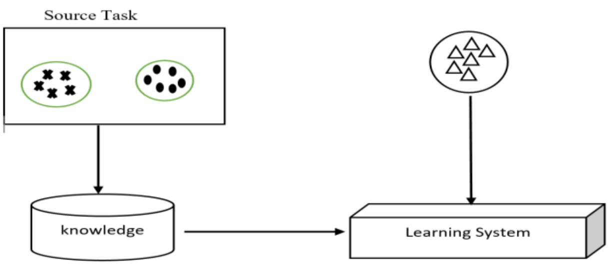


***Fig.** 7. The approach of transfer learning*

Pre-trained models: The convolution neural network (CNN) has a prime vision model which is the visual geometric group (VGG). In 2013, Karen Simonyan and Andrew Zisserman suggest the idea of the VGG. The word VGG comes from the department of Visual Geometry Group at the University of Oxford. VGG16 is a form of CNN that is considered to be one of the top computer vision models. VGG16 is a classification algorithm that is fit to classify various images and is simple to use with transfer learning. Fig. 8 shows the VGG16 architecture and operative layer.

VGG16 makes input sizes 224x244, and convolution layers have a 3x3 filter with stride 1 and used the same padding and max pool layer of a 2x2 filter with stride 2. Both the convolution layer and max pool layers are arranged throughout the whole model. Conv-1 Layer has 64 number of filters, Conv-2 has 128 filters, and Conv-3 has 256 filters. Fully-Connected (FC) layers follow a stack of convolutional layers to perform classification and thus contain many channels (one for each class). The final layer is the soft-max layer.

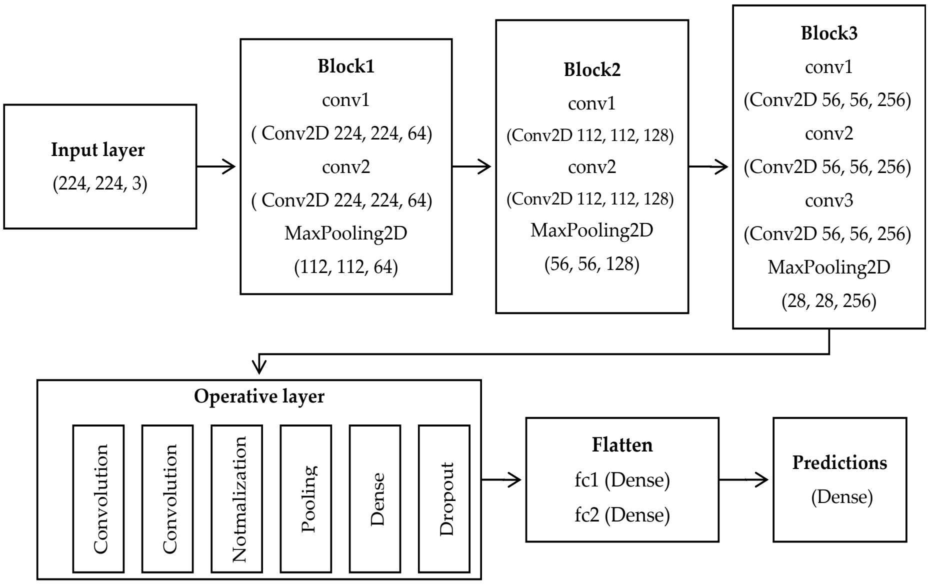


Fig. 8. Data modified model.

4 Numerical Results

An application Programming Interface (API) is a simple method of linking components together through a specific set of instructions. For example, deep learning has an API called Keras which Python used to write it. Keras is not only powerful but also flexible and has more simplicity. Open-source libraries of the machine learning platform have a platform called TensorFlow [39]. In this section, we present the performance of the proposed algorithm on our dataset. All experiments in this paper are executed on a Dell laptop (Intel(R) Core (TM) i7-4600U CPU @ 2.10GHz 2.70 GHz) with 64GB of RAM and NVIDIA (GeForce GT 720M 2GB) using the TensorFlow framework.

Five evaluation metrics were applied to assess the performance of the proposed method[40]. These metrics were sensitivity (tell us about the percentage of total results which had been truly classified by model), specificity (SPE), accuracy (proportion of correct prediction among the total number of cases), precision (tell us about the proportion of input data that are true), and F-score (is the harmonic average of precision and recall). Mathematic representations are:

$$\text{Sensitivity} = \text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \text{ X } 100 \quad (12)$$

$$\text{Accuracy} = \text{ACC} = \frac{\text{TP+TN}}{\text{TP+TN+FN+FP}} \text{ X } 100 \quad (13)$$

$$\text{Specificity} = \text{SPE} = \frac{\text{TN}}{\text{TN+FP}} \text{ X } 100 \quad (14)$$

$$\text{F} - \text{score} = \frac{\text{2TP}}{\text{2TP+FP+FN}} \text{ X } 100 \quad (15)$$

$$\text{Precision} = \text{PPV} = \frac{\text{TP}}{\text{TP+FP}} \text{ X } 100 \quad (16)$$

Where these metrics are evaluated in the terms in Table 2.

Table 2. Confusion matrix parameters.

Predicated Label	Actual Label	Definition
Positive	Positive	TP=True Positive=both actual data and predicated data are true.
Positive	Negative	FP=False Positive=actual data is false but class predicated data is true.
Negative	Positive	FN=False Negative= actual data is true but class predicated data is false.
Negative	Negative	TN=True Negative= both actual and predicated data are false.

After using Python code with Keras library with CNN model (VGG16), we get the following good results.

Table 3 shows that training for a different number of epochs gives significant values of the classification rate [41]. To perform the classification process with a greater accuracy of 0.9935, you need a training time of 2663 seconds.

Table 3. Training results for corona data set.

Epochs	Time Training(s)	Accuracy
4 epochs	2223	0.8882
8 epochs	2227	0.9147
12 epochs	2275	0.9557
16 epochs	2497	0.9856
20 epochs	2663	0.9935

Fig. 9 shows the performance of the confusion matrix for the corona data set with our classification model.

Actual Label		Covid	Other
	Covid	387	3
	Other	1	233

Predicated label

Fig. 9. Confusion Matrix for the covid 19 dataset.

The general performance of classifiers and confusion matrix operators can be seen in Table 4.

Table 4. Performance metrics after training on covid 19 data set.

Data	TP	TN	FP	FN	ACC	RECALL	SPE	PPV	F
Covid	38٧	233	1	3	99.35	99.23	99.57	99.74	99.48
Non covid	233	38٧	3	1	99.35	99.57	99.23	98. 73	99.14

The best accuracy of the proposed method through the fine-tuning process is shown in Fig. 10.

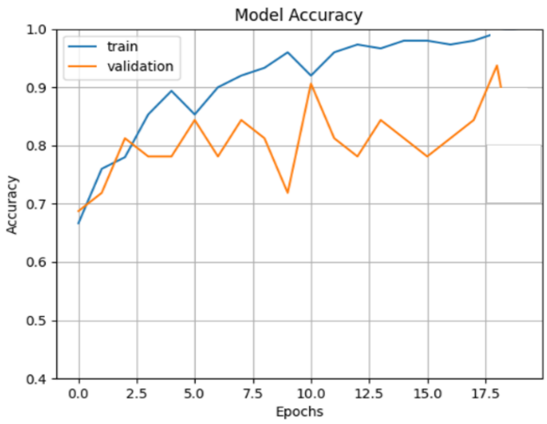


Fig. 10. *The model accuracy of covid dataset*

5- Conclusions

A new area of research is the automatic diagnosis of the disease from medical images based on DL [42]. In the present paper, we have a summary of the CNN architecture with its concepts for classifying medical images. This paper discusses the solution to overcome obstacles in the classification process. Medical images are classified into two steps. The first step is to train the dataset using proposed the model. The second step is the classification operation depending on the results of the training and makes predictions using the suggested model. The proposed model improves the performance by using the lowest error and reducing the classification error and high accuracy compared with other models. Accuracy is 99.35 % of covid 19 images. The future work includes assessing the proposed method with large-scale and different datasets and hybrid with GAN concepts. What if the revised method is used with multiple classifications?

6- References

1. J. Zhang, Y. Xie, Q. Wu, and Y. Xia,: Medical image classification using synergic deep learning. Med Image Anal, vol. 54, pp. 10-19, (May 2019).
2. O. Alshboul, A. Shehadeh, O. Tatari, G. Almasabha, and E. Saleh,: Multiobjective and multivariable optimization for earthmoving equipment. Journal of Facilities Management, no. in press, (2022).
3. O. Alshboul, A. Shehadeh, G. Almasabha, and A. Almuflih, :Extreme Gradient Boosting-Based Machine Learning Approach for Green Building Cost Prediction,. Sustainability, vol. 14, no. 11, pp. 6651, (2022).
4. H. Bae, K. Jang, and Y.K. An,: Deep super resolution crack network (SrcNet) for improving computer vision–based automated crack detectability in in situ bridges. Structural Health Monitoring, vol. 20, no. 4, pp. 1428-1442, (2021).
5. S. Deepa, and B. A. Devi,:A survey on artificial intelligence approaches for medical image classification. Indian Journal of Science and Technology, vol. 4, no. 11, pp. 1583-1595, (2011).
6. S. Mohapatra, T. Swarnkar, and J. Das,: 2 - Deep convolutional neural network in medical image processing. Handbook of Deep Learning in Biomedical Engineering, V. E. Balas, B. K. Mishra and R. Kumar, eds., pp. 25-60: in press, (2021).
7. I. K. E. Purnama, A. K. Hernanda, A. A. P. Ratna et al.: Disease classification based on dermoscopic skin images using convolutional neural network in teledermatology system. In: 2019 International conference on computer engineering, network, and intelligent multimedia (CENIM). IEEE, pp. 1-5, (2019).
8. C. Zheng, X. Deng, Q. Fu et al.: Deep learning-based detection for COVID-19 from chest CT using weak label. In IEEE Transactions on Medical Imaging, vol. 39, no. 8, pp. 2615-2625, Aug. (2020).
9. M. A. Fayemiwo, T. A. Olowookere, S. A. Arekete et al.: Modeling a deep transfer learning framework for the classification of COVID-19 radiology dataset,. PeerJ Computer Science , vol. 7, pp. e614, (2021).
10. L. Tanzi, P. Piazzolla, F. Porpiglia, E. Vezzetti: Real-time deep learning semantic segmentation during intra-operative surgery for 3D augmented reality assistance. International journal of computer assisted radiology and surgery, vol. 16, no. 9, pp. 1435-1445,(2021).
11. J. Zhang, Y. Xia, Q. Wu, Y. Xie,: Classification of medical images and illustrations in the biomedical literature using synergic deep learning. arXiv:1706.09092, (2017).
12. M. Nishio, D. Kobayashi, E. Nishioka et al.: Deep learning model for the automatic classification of COVID-19 pneumonia, non-COVID-19 pneumonia, and the healthy: a multi-center retrospective study. Scientific Reports, vol. 12, no. 1, pp. 8214, (2022).
13. M. Singh, S. Bansal, S. Ahuja et al.: Transfer learning–based ensemble support vector machine model for automated COVID-19 detection using lung computerized tomography scan data," Medical & biological engineering & computing, vol. 59, no. 4, pp. 825-839, (2021).
14. F. Shi, L. Xia, F. Shan et al.: Large-scale screening to distinguish between COVID-19 and community-acquired pneumonia using infection size-aware classification. Physics in medicine & Biology, vol. 66, no. 6, pp. 065031, (2021).
15. H. X. Bai, R. Wang, Z. Xiong et al.: Artificial intelligence augmentation of radiologist performance in distinguishing COVID-19 from pneumonia of other origin at chest CT. Radiology, vol.296, no.3, pp.E156-E165, (2020).
16. D. Singh, V. Kumar, and M. Kaur: Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks. European Journal of Clinical Microbiology & Infectious Diseases, vol. 39, no. 7, pp. 1379-1389, (2020).
17. U. Özkaya, Ş. Öztürk, and M. Barstugan.: Coronavirus (COVID-19) classification using deep features fusion and ranking technique. Big Data Analytics and Artificial Intelligence Against COVID-19: Innovation Vision and Approach, pp. 281-295: Springer, (2020).
18. H. Mukherjee, S. Ghosh, A. Dhar et al.: Shallow convolutional neural network for COVID-19 outbreak screening using chest X-rays. Cognitive Computation, pp. 1-14, (2021).
19. F. Saberi-Movahed, M. Rostami, K. Berahmand et al.: Dual Regularized Unsupervised Feature Selection Based on Matrix Factorization and Minimum Redundancy with application in gene selection. Knowledge-Based Systems, vol. 256, pp. 109884, (2022).
20. S. Laddha, S. Mnasri, M. Alghamdi et al.: COVID-19 Diagnosis and Classification Using Radiological Imaging and Deep Learning Techniques: A Comparative Study. Diagnostics, vol. 12, no. 8, pp. 1880, (2022).
21. P. Aggarwal, N. K. Mishra, B. Fatimah et al.: COVID-19 image classification using deep learning: Advances, challenges and opportunities. Computers in Biology and Medicine, pp. 105350, (2022).

22. M. O. Arowolo, R. O. Ogundokun, S. Misra, A. F. Kadri, and T. O. Aduragba.: Machine learning approach using KPCA-SVMs for predicting COVID-19. Healthcare informatics for fighting COVID-19 and future epidemics, pp. 193-209: Springer, (2022).
23. L. Muhammad, E. A. Algehyne, S. S. Usman et al.: Supervised machine learning models for prediction of COVID-19 infection using epidemiology dataset. SN computer science, vol. 2, no. 1, pp. 1-13, (2021).
24. R. Yan, F. Ren, Z. Wang et al.: Breast cancer histopathological image classification using a hybrid deep neural network. Methods, vol. 173, pp. 52-60, (2020).
25. M. Murata, Y. Ariji, Y. Ohashi et al.: Deep-learning classification using convolutional neural network for evaluation of maxillary sinusitis on panoramic radiography. Oral radiology, vol. 35, no. 3, pp. 301-307, (2019).
26. N. Khasawneh, M. Fraiwan, L. Fraiwan, B. Khassawneh, and A. Ibnian,: Detection of COVID-19 from Chest X-ray Images Using Deep Convolutional Neural Networks. Sensors, vol. 21, no. 17, pp. 5940, (2021).
27. O. A. Montesinos-López, A. Montesinos-López, P. Pérez-Rodríguez et al.: A review of deep learning applications for genomic selection. BMC genomics, vol. 22, no. 1, pp. 1-23, (2021).
28. Kaggle Covide data base https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia , last accessed 2021/4/14.
29. D. Cozzi, M. Albanesi, E. Cavigli et al.: Chest X-ray in new Coronavirus Disease 2019 (COVID-19) infection: findings and correlation with clinical outcome. La radiologia medica, vol. 125, no. 8, pp. 730-737, (2020).
30. R. Chandel, and G. Gupta: Image filtering algorithms and techniques: A review. International Journal of Advanced Research in Computer Science and Software Engineering, vol. 3, no. 10, (2013).
31. J. Amin, M. Sharif, N. Gul, S. Kadry, and C. Chakraborty.: Quantum machine learning architecture for COVID-19 classification based on synthetic data generation using conditional adversarial neural network.Cognitive Computation, vol. 14, no. 5, pp. 1677-1688, (2022).
32. Activation function. https://www.v7labs.com/blog/neural-networks-activation-functions last accessed 2021/8/10.
33. Comparison Functions. https://www.aitude.com/comparison-of-sigmoid-tanh-and-relu-activation-functions/ , last accessed 2021/3/15.
34. K. Santosh, S. Ghosh, and D. GhoshRoy.: Deep learning for covid-19 screening using chest x-rays in 2020: A systematic review. International Journal of Pattern Recognition and Artificial Intelligence, vol. 36, no. 05, pp. 2252010, (2022).
35. A. Rosebrock, Deep Learning for Computer Vision with Python, 1.2.1 pp. 323: PYIMAGESEARCH, (2017).
36. S. J. P. Singh.: Fully Connected Layer: The brute force layer of a Machine Learning model. OpenGenus IQ: Learn Computer Science, vol. 2, pp. 2021, (2019).
37. J. Brownlee.: A gentle introduction to batch normalization for deep neural networks. Machine learning mastery, vol.4, (2019).
38. S.Tammina.: Transfer learning using vgg-16 with deep convolutional neural network for classifying images. International Journal of Scientific and Research Publications (IJSRP), vol. 9, no. 10, pp. 143-150, (2019).
39. M. Abadi, A. Agarwal, P. Barham et al.: Tensorflow: Large-scale machine learning on heterogeneous distributed systems. arXiv:1603.04467, (2016).
40. G. Canbek, T. Taskaya Temizel, and S .Sagiroglu,: BenchMetrics: a systematic benchmarking method for binary classification performance metrics. Neural Computing and Applications, vol. 33, no. 21, pp. 14623-14650, (2021).
41. S. Sinha, T. Singh, V. Singh, and A.Verma,: Epoch determination for neural network by self-organized map (SOM). Computational Geosciences, vol. 14, no. 1, pp. 199-206, (2010).
42. L. Tan, X. Guo, S. Ren, J. N. Epstein, and L.Lu,.: A computational model for the automatic diagnosis of attention deficit hyperactivity disorder based on functional brain volume. Frontiers in computational neuroscience, vol. 11, pp. 75,(2017).