CCBlock Based On Deep Learning for Diagnosis COVID-19 In Chest X-Ray Images

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Abstract

Purpose: COVID-19 pandemic continues to hit countries one after the other and has dramatically affected the health and well-being of the world's population. With the daily increase in the number of people with this disease, the impressive speed of spread and the delay in the results of PCR analysis, it may cause the disease to spread more broadly. Therefore it is necessary to consider finding alternative methods of detection and diagnosis COVID-19 to prohibit the spread of the disease among people. Convolutional Neural Network (CNN) automated detection systems have shown auspicious results in detecting patients with COVID-19 through radiography; thus, we suggest them as an alternative option to diagnose COVID-19.

Method: In this study, an early screening model based on the enhancement of classical Visual Geometry Group Network (VGG) with Convolutional Covid Block (*CCBlock*) was proposed to detect and distinguish COVID-19 from Pneumonia, and healthy people using chest X-ray radiographs. The data set used for model testing is the x-ray images available on public platforms, which consist of 1,828 x-ray images, including 310 images for confirmed COVID-19 patients, 864 images for pneumonia patients, and 654 images for healthy people.

Results: The experiment result of the dataset showed that the added enhancements to the classical VGG network with X-ray imaging provide the highest detection performance and overall accuracy of 98.52% for two classes and 95.34% accuracy for three classes.

Conclusions: Considering the achievement results obtained, it was found that utilizing the enhanced VGG deep neural network helps radiologists automatically diagnose COVID-19 in X-ray images.

Keywords: COVID-19, X-ray radiographs, Transfer learning, Deep learning, Automatic detection.

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Introduction

In December 2019, The COVID-19 pandemic in Wuhan, China, appeared [1-4]. The epidemic features had a devastating impact on the health and welfare of the world's population and are still killing people. Additionally, it has affected the economy of nations where the disease has spread. Coronavirus belongs to an outsized group of dangerous viruses [5] that cause illnesses caused by the cold, such as SARS coronavirus (SARS-CoV). One of these families is COVID-19. The World Health Organization (WHO) named the infectious disease caused by this type of viruses as COVID-19 on Feb 11, 2020 [6]. This strange virus cannot be understood a lot because its behavior is entirely different. Coronavirus is of an animal origin due to infection from animals to humans [7]. The Covid-19 virus is believed to have passed from bats to humans [8]. Respiratory transmission of the disease from person to a person causes the rapid spread of the epidemic.

Common symptoms of individuals with this disease are cough, fever, dyspnea, muscle pain, and fatigue [9]. COVID-19 causes severe respiratory symptoms and is related to high Intensive Care Unit (ICU) admission. In more severe cases, the infection can cause pneumonia, severe acute respiratory syndrome, septic shock, multi-organ failure, and death [7,9] Due to the rapid spread of COVID-19, the step to limit its range is the early detection of the disease. The primary test method used to detect COVID-19 is a Polymerase Chain Reaction (PCR) [10], which can detect SARS-CoV-2 RNA from respiratory specimens (collected through the spread of passages like the pharyngeal or pharyngeal tracts). This mean the diagnosis of COVID-19 should be confirmed by gene sequencing for respiratory or blood specimens as a critical indicator for Reverse Transcription Polymerase Chain Reaction (RT-PCR) or hospitalization. The PCR test is an essential standard because it is susceptible. However, it is time consuming, stressful, complicated, and provided only for a brief time. Therefore, medical imaging procedures like Chest X-ray (CXR) and Computerized Tomography (CT) can play a severe role in diagnosing positive COVID-19 patients because radiography examination is fast and available given the spread of chest radiology imaging systems in modern healthcare systems On the other hand, previous studies have shown that images of patients with Covid-19 virus show abnormal abnormalities [8, 11] .

The main disadvantage of using CT imaging is the high patient dose and costs of scanning. In contrast, conventional radiograph or CXR machines are available in hospitals and clinics to produce 2-dimensional (2D) projection images of the patient's thorax. Therefore, it is suggested that the chest radiography test can be used as the primary detection tool for Covid-19 [12]. Thus, in this study, an X-ray imaging technique is suggested for potential COVID-19 patients.

Digital image processing technology has been widely applied in the medical field, including organ segmentation and image enhancement and repair, providing Initial support for subsequent diagnosis [13, 14]. With the rapid development of Artificial Intelligence (AI), Deep learning techniques associated with automatic diagnosis in the medical field have spread widely, as they have become a useful tool for medical specialists. Deep learning techniques has been used in many medical applications such as breast cancer detection [15], classification of brain diseases [16], detection of pneumonia [17] etc. With the unexpected appearance of the Corona epidemic in the world and the disproportionate numbers of patients with the preparation of diagnostic medical staff, researchers in the field of artificial intelligence must harness their capabilities to detect this disease and limit its spread.

Recently, numerous research has been suggested to automatic COVID-19 diagnosis, we will describe some of these related studies and discuss their results in the Results section.

Ioannis et al. [18] suggested to using transfer learning with deep model to diagnose a COVID-19 epidemic. Their model achieved good accuracy for classifying two classes and three classes, respectively. Tulin et al.[19] suggested in their study, the (DarkNet) Model as a classifier. This model, they used 17 convolutional layers with different filtering. Linda Wang, et al. [20] proposed a deep convolutional neural network, namely (COVID-Net), which they create utilizing a human-machine collaborative design strategy, and they also collected a 13800 data set of chest x-ray images called (COVIDx). Hamdan et al.[21] presented (COVIDX-NET) framework depended on seven deep neural networks such as (VGG-19, DenseNet121, ResNetV2, etc) to train the dataset and diagnose COVID-19. Ali Narin et al.[22] used pre-trained convolutional neural network-based models (ResNet50, InceptionV3, and Inception ResNetV2) to predict a small set of data. Research of Prabira Kumar Sethy et al. [23] differs from the researches mentioned above in terms of the work strategy where the deep features extracted by a deep convolutional network (ResNet50) then classified COVID-19 disease from the remainder of the chest x-ray images using Support Vector Machine (SVM). Because of the limited data available, Pedro Bassi et al. [24] also benefited from the transfer learning strategy and provided a deep neural network (CheXNet) that's pre-trained in images of 14 chest diseases. CheXNet is DenseNet121, trained on ImageNet, and trained again on 14 classes of chest x-rays image.

Also, there are many other studies to diagnose COVID-19 based on deep neural networks with CT scan images [25-29].

However, the use of deep learning techniques to identify and detect COVID-19 in X-rays is still minimal and has reasonable accuracy. As a result, driven by the necessity for a faster interpretation of radiography images, we propose

an automatic prediction and distinguishes COVID-19 from Pneumonia, and healthy people based on the enhancements to the classical VGG network with X-ray radiographing.

Methods section discusses the methodology used to create the proposed network, Transfer learning, and general clarifications of the deep convolutional neural network that we used, As well as, the architecture of VGG network enhancement. Experiments and results section, which includes a general review of the dataset that used in experiments, and presents the results of experiments conducted to evaluate the efficacy of the proposed VGG enhancement network, and compared it with the previous related works. In the discussion section, we will discuss the results of experiments and the limitations of this study. Finally, conclusion section, we will explain the main conclusions and the importance of this study.

Method

Transfer Learning

It is a strategy by which the knowledge extracted by the neural network is transferred from specific data to solve a different issue. Still, it is related to a new task that includes new data that is usually not sufficient to train neural networks from the beginning [33].

In deep learning, the availability of large and sufficient numbers of data is necessary for proper training of neural networks, as the availability of data for initial training is an essential factor for the success of the CNN training process to extracting the distinct characteristics of the images. As for the lack of a sufficient number of training data, as in the medical image data, we resort to the ability of neural networks trained in a sufficient data set to extracting the essential characteristics, to extract the characteristics of the images, and this is called transfer of learning. There are two strategies for transferring learning.

The first is to use neural networks to extract important characteristics in data while retaining the trained network architecture, where the trained network outputs are the data properties, that given to the classifier network [34]. As for the second strategy, it depends on adjusting the network architecture and using its pre-trained weights and attaching to a parallel architecture that contains untrained weights that were trained using the available data, and that used in this study. The most popular neural networks that use transfer learning for medical tasks are ImageNet-trained networks used in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [35]. Among the networks trained on this database used in medical tasks are VGG-16, VGG-19, Res-Net, etc.

Deep Learning Classifiers

In this section of the paper, we describe the deep classifications used in this study that will be used in experiments.

VGG-Net: This network was developed, and built-in 2014 by K. Simonyan and A. Zisserman [36] for Challenge (ILSVRC2014) as this network performed well in ImageNet data classification, and there are two versions of this network architecture that are different in depth. The first is VGG-16, which contains 13 convolution layers, three fully connected layers, and five pooling layers. The second is VGG-19, which contains 16 convolution layers, three fully connected layers, and five pooling layers.

The proposed model

Deep learning has brought about a breakthrough in the areas of artificial intelligence, such as diagnosing pictures, people, and sounds. As the word deep indicates an increase in the number of layers. A model that uses one or more hidden layers is called a deep model. These are called CNN models, which mean a convolutional neural network. Where convolutional denotes the presence of convolutional layers that contain a set of filters that have weights that are trained using learning data and the benefit of which is to extract the input characteristics. Another important layer is the fully connected layers, which are at the end of the network and contain a set of weights that are trained using training data in the training phase. There are other layers called activity layers, including the non-linear activity layer (ReLu), which works to delete negative values.

Neural networks are trained using a set of enhancers, the most important of which is the Stochastic Gradient Descent (SGD), which works at the expense of the derivative of the error, for use in the process of updating the weights in the layers of the deep model, as in the convolutional layers and fully connected layers. Since updating weights with a dependent error derivative and a small learning rate is the training process. Training from beginning convolutional neural networks requires large amounts of data, which in medical diagnostic tasks are usually not sufficiently available. Despite the rapid and widespread prevalence and the large number of patients with COVID-19 that, due to the conditions that accompany this pandemic, it became not possible to collect enough data to train neural networks from begin, so we content ourselves with the few data available on different platforms.

It is not necessary to build a deep model from the beginning. It is possible to use pre-built models, for example (VGG-16, VGG-19, ResNet, and etc.)) And modify them. In this study, we selected and modified the model (VGG-16). We added three convolutional layers, each one followed by ReLu and Batch Normalization layer. Making this modification will improve the classification process due to the presence of several of untrained filters that will be trained using the training data.

The added convolutional layers have the number of filters (512,256,128), respectively. This model is a similar model to the model (VGG-19) in a number of learnable layers. The model (VGG-19) has 19 learnable layers that contain weights that are trained using training data. The original model (VGG-16) contains 16 learnable layers. In this study, one of the fully connected layers in the basic model was deleted, bringing the number of learnable layers to 15. The proposed model is similar to the model (VGG-19) in terms of the number of convolutional layers are used; these three added layers we named it *Convolutional COVID Block (CCBlock).*

As mentioned in the Learning Transfer section, it is possible to use pre-trained networks in different strategies. In this study, the second strategy was used that allows the use of pre-trained networks as part of the deep model where the part added to the model is trained using training data in the study. Table 5 shows the layers used for the proposed model with all its properties.

Table 5 the layers and their properties for the proposed model (for two or three categories)

Layer		Feature map	Size	Trainable	Pre-Trained
input	Image	1	224x224x3	False	False
1	2xConvolution	64	224x224x64	True	True
2	Maxpooling	64	112x112x64	False	False
3	2xConvolution	128	112x112x128	True	True
4	Maxpooling	128	56x56x128	False	False
5	2xConvolution	256	56x56x256	True	True
6	Maxpooling	256	28x28x256	False	False
7	3xConvolution	512	28x28x512	True	True
8	Maxpooling	512	14x14x512	False	False
9	3xConvolution	512	14x14x512	True	True
10	Maxpooling	512	7x7x512	False	False
11	**1xConvolution**	512	5x5x512	True	False
12	**BatchNorm**	512	5x5x512	True	False
13	**1xConvolution**	256	3x3x256	True	False
14	**BatchNorm**	256	3x3x256	True	False
15	**1xConvolution**	128	1x1x128	True	False
16	**BatchNorm**	128	1x1x128	True	False
17	Flatten	128	1x128	False	False
18	FC	-	1x256	True	False
19	FC+Softmax	-	1x3 or 1x2	True	False

Results

Dataset

In order to develop any diagnostic tool, sufficient data must be available to improve this tool. In order to overcome the paucity of X-ray images of COVID-19 patients, we used three different open sources to collect a sufficient number of X-ray images to train and test the proposed network. The data set is an x-ray images of the human chest taken by the widely available X-ray machine. One of the challenges that we can face in training networks is the imbalance of data, therefore we do a balance in preparing data set images. We used 1828 chest x-ray images. The first of the three sources used in the study was Dr. Cohen, who collected data from public sources that did not violate patient privacy.

We extracted 241 chest x-ray images for the COVID-19 patients from Dr. Cohen's dataset [30]. The view of these images was from different sides, which is the posteroanterior (PA), anteroposterior (AP), laying down (AP Supine), and lateral (L). The second source used in this study is from the Kaggle platform. Data for this source contained 79 chest X-rays for COVID-19 patients [31]. It is noteworthy; there are ten similar images between the two sources, so they were deleted, and bringing the total number of chest x-ray for patients COVID-19 is 310 images. The third source is also from the Kaggle platform, which contains a broad set of chest x-rays for patients with pneumonia and healthy people [32]. From these data, we took 864 chest x-rays of pneumonia patients, included 467 images of bacterial pneumonia, and 397 images of patients with viral pneumonia. Also 654 chest x-ray images of healthy people were taken from the same data set. We divided the dataset into two parts, the training set and the testing set, which was 27% for the training the proposed model and 73% for testing it, as in Table 1.

Table 1 Database details

	COVID-19	**Pneumonia (Virus Bacterial)**	**Normal**
Train	84	233	176
Test	226	631	478
Train + Test	310	864	654

Experiments

In this study, we performed tests to diagnose and classify COVID-19 using a chest x-ray. tests performed on two types of database group: the first type that includes two categories (COVID-19, Normal) and the second type includes three categories (COVID-19, Normal, and Pneumonia), the data set was divided into two parts 27% as training data and 73% as test data. To evaluate the efficiency and stability of the proposed model, the tests were repeated five times for both types of data. The optimizer (SGD) used with a 0.001 learning rate, batch size 32, Momentum 0.9, and epochs 30.

This study was performed using Python and Keras package with TensorFlow on Intel (R) Core (TM) i7-5700HQ CPU @ 2.70GHz (8 CPUs), ~ 2.7GHz. Also, besides, the experiments were performed using the NVIDIA GTX 970M GPU and RAM with 8 GB and 16 GB, respectively.

In Fig.1, the graph of classification losses and accuracy for training and testing stages.

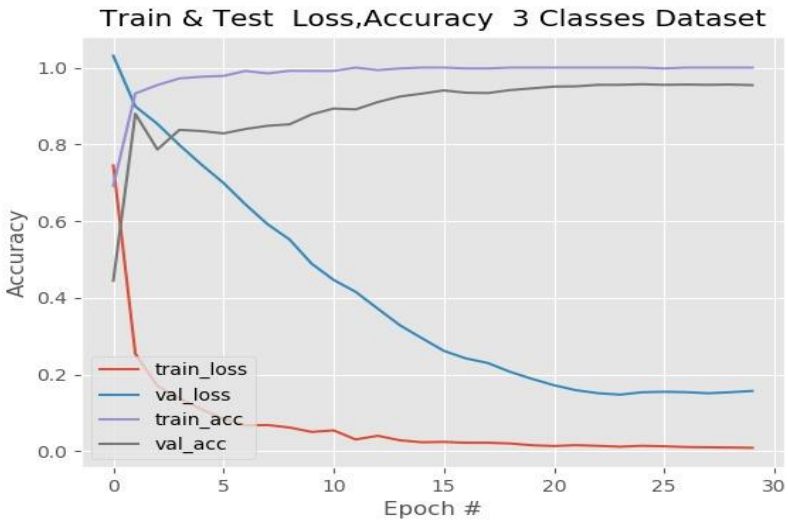

Fig.1 graph of classification losses and accuracy of the proposed model

Fig.1 shows that the amount of training losses decreases rapidly, as it recorded a rate of losses of approximately 0.1 during the first five epochs and continued downward until it reached nearly zero after 25 epochs. As for the rate of test losses, its descent was less steep, and this is normal because the data that tested proposed model were new data. As for the accuracy scheme, it is clear that the proposed model can generalize, as the scheme has a slight difference between the accuracy of training and testing, and this is a good indication of the efficiency of the proposed model *CCBlock*.

To evaluating proposed model *CCBlock*, a confusion matrix was calculated for each implementation, as shown in Fig.2 Fig.3. The results showed that the proposed model has the efficiency and high stability of the diagnosis COVID-19 for categories (Normal and Pneumonia) well, we have documented the rate of 98.52% accuracy on the two and 95.34% on the three categories. Amounts Sensitivity, specificity, and accuracy three categories and five implementation times in Table 2, and two categories in Table 3.

Table 2 Sensitivity, Specificity, and accuracy for three categories

	Sensitivity	**Specificity**	**Accuracy**
Run1	98.21	98.94	95.21
Run2	99.10	98.72	95.43
Run3	99.10	99.15	95.43
Run4	96.85	99.36	95.13
Run5	99.10	98.72	95.51
average	**98.47**	**98.98**	**95.34**

Table 3 Sensitivity, Specificity, and accuracy for two categories

	Sensitivity	**Specificity**	**Accuracy**
Run1	98.67	98.54	98.58
Run2	98.23	98.54	98.44
Run3	98.67	97.70	98.01
Run4	98.66	98.95	98.86
Run5	98.67	98.74	98.72
average	**98.58**	**98.49**	**98.52**

It is apparent in table 3 that the proposed model proved useful in the diagnosis and classification of COVID-19 from classes (Normal, Pneumonia). Where we recorded accuracy of 95.51% as the highest accuracy obtained. However, we decided to take an average of 5 implementation times, where a rate of 95.34% was obtained. To test the

efficacy of the proposed model on the diagnosis and classification of COVID-19, we tested our proposed model *CCBlock* on the second database, which includes x-rays of people with COVID-19 and pictures of uninfected people. Where we recorded 98.86% as the highest accuracy for the proposed model, but we considered taking the average for five times implementation and considering it the accuracy of the proposed model, where the average accuracy 95.34% was recorded.

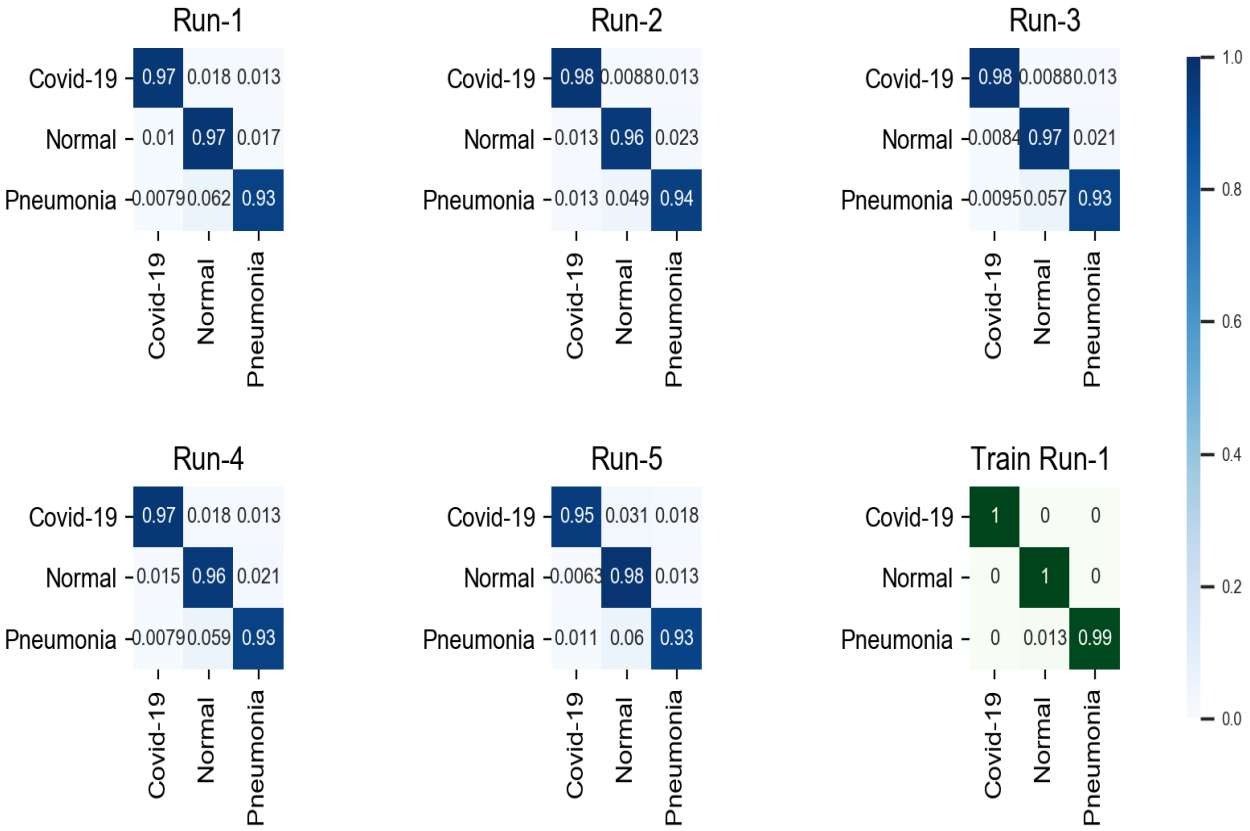

Fig.2 confusion matrix of the proposed three-class model

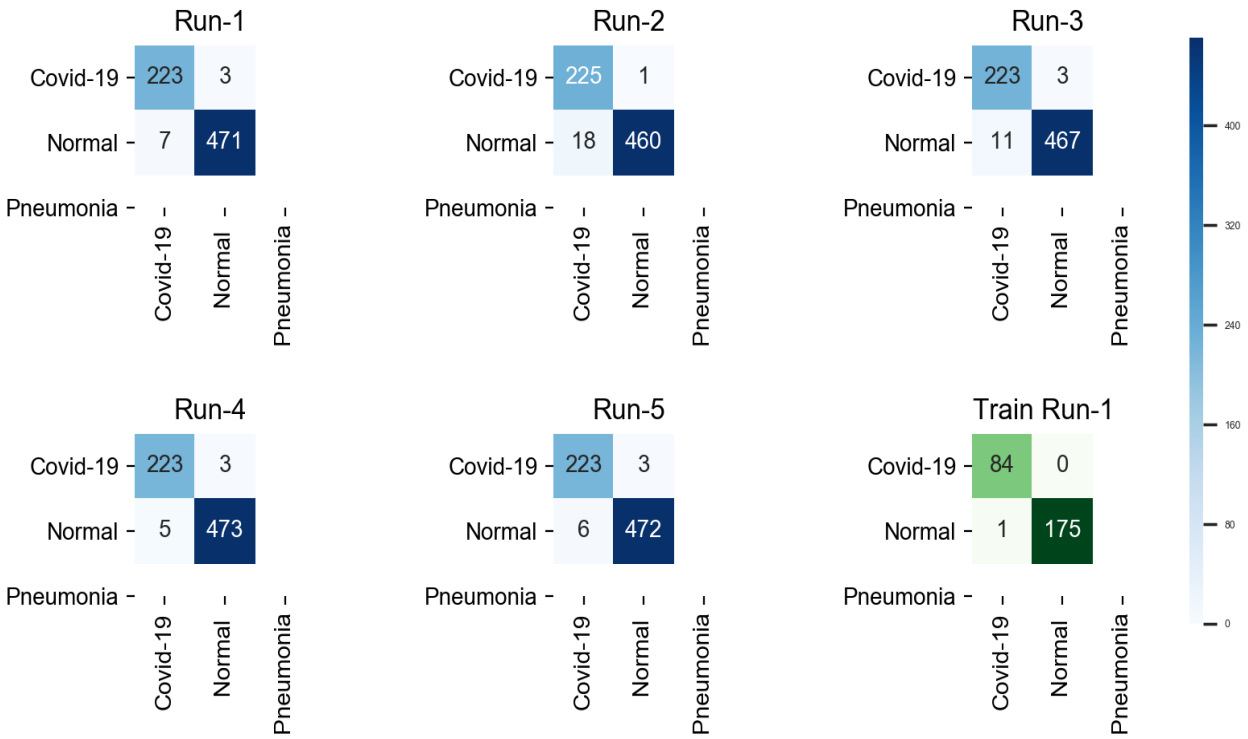

Fig.3 confusion matrix of the proposed two-class model

In the field of machine learning and specifically in matters of classification, a confusion matrix is one of the methods that allows a more precise visualization of the performance of the algorithm, as it shows errors of a classification algorithm for each category with other categories. The primary diameter of the array represents the classes that were correctly categorized, while the other elements represent the data that incorrectly classified as other categories. In Fig.3 we calculated the confusion matrix for each implementation on the first data set that includes the three categories (COVID-19, Normal, and Pneumonia). Fig.3, shows that the proposed model is highly capable of diagnosing COVID-19 from other categories. We recorded the highest rating accuracy for COVID-19 (98%). Whereas, the Train Run-1 matrix shows the COVID-19 classification for the first implementation using the proposed model on the training data for three categories.

In Fig.3, the confusion matrix of a set of tests performed on the second data set, which includes two categories (COVID-19, Normal). In this study, we focus on COVID-19, so it is best to test the proposed *CCBlock* model ability in diagnose COVID-19 from those who are not infected. Confusion Matrix showed that the proposed model was able to record a diagnostic accuracy of COVID-19 of 99.55%. Whereas, the Train Run-1 matrix shows the COVID-19 classification for the first implementation, using the proposed model on the training data for, two categories.

The results obtained in previous studies showed the proficiency of deep neural networks in the diagnosis and classification of COVID-19 well from other categories. However, our proposed model *CCBlock* proved its worth and superiority over previous studies in both issues two categories and three categories where we recorded a higher accuracy than the accuracy of previous studies, as shown in table 4.

Table 4 Comparison between the proposed model and previous studies

Study	Type of Images	Number of Cases	Method Used	Accuracy 2-classes (%)	Accuracy 3-classes (%)
Ioannis et al. [18]	Chest X-ray	224 COVID-19(+) 700 Pneumonia 504 Healthy	VGG-19	-	93.48
Tulin et al. [19]	Chest X-ray	125 COVID-19(+) 500 No-Findings 125 COVID-19(+) 500 Pneumonia 500 No-Findings	DarkCovidNet	98.08	87.02
Wang and Wong [20]	Chest X-ray	53 COVID-19(+) 5526 COVID-19 (-) 8066 Healthy	COVID-Net	-	92.4
Hemdan et al. [21]	Chest X-ray	25 COVID-19(+) 25 Normal	COVIDX-Net	90.0	-
Narin et al. [22]	Chest X-ray	50 COVID-19(+) 50 COVID-19 (-)	Deep CNN ResNet-50	98	-
Sethy and Behra [23]	Chest X-ray	25 COVID-19(+) 25 COVID-19 (-)	ResNet50+ SVM	95.38	-
Zheng et al. [26]	Chest CT	313 COVID-19(+) 229 COVID-19(-)	UNet+3D Deep Network	90.8	-
Wang et al. [27]	Chest CT	195 COVID-19(+) 258 COVID-19(-)	M-Inception	82.9	-
Xu et al. [28]	Chest CT	219 COVID-19(+) 224 Viral pneumonia 175 Healthy	ResNet+Location Attention	-	86.7
Ying et al [29]	Chest CT	777 COVID-19(+) 708 Healthy	DRE-Net	86	-
Proposed Study CCBlock	Chest X-ray	310 COVID-19(+) 654 Healthy 864 Pneumonia(virus &bacteria)	VGG-16+CCBlock	98.86	95.51

Discussion

One of the most critical problems facing researchers in the use of deep learning in the field of diagnosis or treatment of medical images is the lack of data available in such tasks. Therefore, researchers tend to use deep learning with the transferred learning strategy to solve this problem. As sufficient numbers of images or data are available to train the deep model is necessary. In this study, the VGG-16 + *CCBlock* model is proposed in two parts: the first part (VGG-16) that uses a transfer learning strategy. The second part (*CCBlock*): which was trained from the beginning using the available training data mentioned in the database section. Because of the conditions that accompany the COVID-19 pandemic, it became impossible to collect sufficient data on the pandemic, so most researchers relied on the COVID-19 data set available on the Kaggle platform.

Conclusion

The use of deep neural networks has proven to be useful in diagnosing respiratory diseases in X-ray images of the patient's chest. In this study, a model for diagnosing COVID-19 infection using a transfer learning strategy proposed. We added (*CCBlock*), (VGG-16) trained on the image (ImageNet) and obtained excellent results to confirm the infection with Virus COVID-19. As experiments have proven that the proposed model has high efficacy in diagnosing the COVID-19 virus, 98.86% accuracy was recorded for two categories (COVID-19, Normal) and 95.51% accuracy for three categories (COVID-19, Normal, Pneumonia).

Looking at the results makes us think that X-ray experts can be helped in making a decision using the proposed model. Despite the high accuracy of computer-aided diagnosis, laboratory tests such as PCR cannot be dispensed with, but these results can be used to assist and support laboratory results. In the future, if sufficient data are available, deep neural networks can be trained from the start, leading to better results without the need for a transfer learning strategy.

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