A Deep Learning Approach for Covid-19 Detection in Chest X-Rays

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Abstract
The novel coronavirus 2019 is called COVID-19 has outspread swiftly worldwide. An early diagnosis is more important to control its quick spread. Medical imaging mechanics, chest calculated tomography or chest X-ray, are playing a vital character in the identification and testing of COVID-19 in this present epidemic. Chest X-ray is cost effective method for Covid-19 detection however the manual process of x-ray analysis is time consuming given that the number of infected individuals keep growing rapidly. For this reason, it is very important to develop an automated COVID-19 detection process to control this pandemic. In this study, we address the task of automatic detection of Covid-19 by using a popular deep learning model namely the VGG19 model. We used 1300 healthy and 1300 confirmed COVID-19 chest X-ray images in this experiment. We performed three experiments by freezing different blocks and layers of VGG19 and finally, we used a machine learning classifier SVM for detecting COVID-19. In every experiment, we used a five-fold cross-validation method to train and validated the model and finally achieved 98.1% overall classification accuracy. Experimental results show that our proposed method using the deep learning-based VGG19 model can be used as a tool to aid radiologists and play a crucial role in the timely diagnosis of Covid-19.
Keywords:
Convolutional Neural Networks, X-ray, COVID19, Transfer-Learning,Deep-Learning

1. Introduction

At the end of 2019, the people of the world were confronted with an epidemic disease of the respiratory syndrome called COVID-19 that the people didn't anticipate coming upon in the modern generation of technology. The novel Coronavirus is known as SARS-CoV-2 or 2019-nCoV or COVID-19 has become a serious common health problem in the world. In December 2019, it was initially identified in Wuhan, China [1, 2]. Coronavirus has a large family; COVID-19 is one of them that can attack both animals and humans [3] which creates respiratory disease. Other frequent coronaviruses recognized in the previous are SARS-CoV and MERS-CoV in the Middle East, which were almost 8100 and 2500 verified incidents, and the death rate of approximately 9.2% and 37.1% respectively [4, 5].

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At the time of writing (March 12, 2021), around 224 countries are affected by COVID-19. The total number of affected cases, death cases worldwide has around 124.1 million, 2.71 million respectively, and around 98.5 million people are recovered from this epidemic disease and plunging mankind into a serious condition of dread whose result is yet uncertain [6].

Generally, the virus of COVID-19 spreads when infected people come to close contact with another people. Aerosols and small droplets carry the virus which is easily spread out from an affected person's mouth and nose when they talk, breath, cough, sing, or sneeze. The virus might also additionally unfold with the aid of contaminated surfaces, though this is no longer notion to be the primary route of transmission [7, 8]. A wide variety of symptoms have been reported by people with COVID-19, ranging from mild symptoms to serious illness. Symptoms can occur 2-14 days after the virus has been revealed. People may have COVID-19 with these symptoms: cough, chills or fever, shortness of breath or difficulty breathing, tiredness, arches in body and muscle, headaches, fragrance, sore throat, diarrhea, nausea or vomiting, congestion, or runny nose. In some serious situations, the infection can create multi-organ failure, pneumonia, septic shock, exquisite respiratory syndrome, and death [9].

The number of tools that were handy to doctors and medical experts battling with the disease was inadequate when the COVID-19 outbreak started in China. In many developing countries, the health management system has arrived at the disappointment stage for the growing requirement of exquisite care units. At the same time, the medicals and clinics are packed with COVID-19 patients that are getting worse. On the other hand, COVID-19 tests are generally difficult because there are not enough test kits for people and the small knowledge of COVID-19 creates panic among them. The unethical people take advantage to sell fake COVID-19 testing kits to panicked people after locating them from different social sites. We need to rely on other diagnostic methods to detect COVID-19, considering that there are restricted COVID-19 testing tools. Besides, it is tough to provide proper health treatment to a large number of people because the virus has a highly infectious nature and it infected people very quickly. Consequently, initial detection and monitoring of the distribution of COVID-19 are terrifically difficult [10].

If we want to control the epidemic situation and prevent the virus from outspreading, the initial detection of COVID-19 is significant. Modern analytic tests for COVID-19 incorporate opposite record Polymerase Chain Response, real-time RT-PCR, and opposite record circle mediate isothermal intensification (RT-LAMP) [11, 12]. COVID-19 chest scan is an example of the unmistakable pneumonia method to reduce the COVID-19 testing time. Through this strategy, doctors and medical specialists will more quickly find isolation and treatment options for patients.

Patients could get a negative outcome from the RT-PCR test when they are affected by the virus and present serious indications [11]. In this situation, different medical imaging methods like chest X-rays or chest calculated tomography are used to COVID-19 diagnoses. Even though CT has ended up being perhaps the most exact diagnostic process for COVID-19 [13], which has some significant restrictions, including significant cost, around 70× maximum ionizing radiation than X-ray [14], and the way that it can't have proceeded as a bedside test. In this manner, it isn't regularly utilized in COVID-19 determination [15]. Additionally, it isn't appropriate for checking the advancement of explicit cases, especially in basically sick patients. X-ray is a less delicate methodology to detect COVID-19 when contrasted with 69% revealed pattern sensitivity of CT [16]. X-ray is a less expensive and faster option and it is additionally accessible in most clinics. On the other hand, X-rays will probably be the technique of imaging method needed to analyze and identify COVID-19 patients. Moreover, these strategies may introduce limitations in specific patients, for example, pregnant women, as they may harm unborn babies [17].

COVID-19 is an exceptionally current issue; many researchers already have experimented with discovering solutions in a time of these emergencies. Artificial Intelligence-based mechanized CT image analysis apparatuses have been created for the detection, observing of COVID-19, and identifying affected patients from disease-free patients [18]. Using chest CT scan a deep learning-based method was developed by Fei [19] for contamination destinations and programmed division of all lungs. By using deep-learning techniques and aspiratory CT scan images Xiaowei proposed a screening model for early recognition of COVID-19 pneumonia and Influenza [20]. From the study of changing radiographic images of COVID-19 from CT images, Shuai built up a deep learning-based framework that can reduce the crucial time for the infection finding and remove COVID-19 graphical highlights before pathogenic testing to give clinical determination [21].

1. In this paper, we have proposed a method for the automatic detection of COVID-19 using chest X-ray images with the VGG19 model. We can easily collect chest X-ray images because images are available in hospitals. For this reason, it is easily possible to use the proposed method to test COVID-19 using chest X-ray images.

The main key points of this paper are summarized as below:

- We proposed a deep learning method by using an effective pre-trained VGG19 model to detect Covid-19.
- The model has been appeared to get high outcomes in the chest X-ray dataset (1300 COVID-19 vs. 1300 healthy).
- For better performance, we don’t use the total blocks and layers of VGG19. We use some convolutional blocks and fully connected layers of VGG19 and perform three experiments in three ways.
- We freeze the convolutional blocks and fully connected layers to reduce time complexity for Covid-19 detection.
- In our experiment, we freeze convolutional block_1, convolutional block_2 and use fully connected layer_1 (FC_1), fully connected layer_2 (FC_2), and fully connected layer_3 (FC_3) of VGG19 model. In the first experiment, we use the FC_1, FC_2 layers and freeze FC_3 layer. Then we use the FC_2, FC_3 layers and freeze FC_1 layer. At last, we use the FC_1, FC_3 layers and freeze FC_2.
- Finally, we use the SVM classifier for classifying chest X-ray images as covid-19 positive or not and show that our proposed method provides a better result to detect COVID-19 in a short time and our method is more useful for medical experts and doctors for their work.

The remaining section of the paper is classified as follows:

- The literature review is discussed in section 2.
- Section 3 covers dataset description.
- The proposed methodology is presented in section 4.
- Section 5 briefs the exploratory result and discussion.
- Finally, the conclusion of the experiment is covered in section 6.
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2. Literature Review

In this part, we analyzed a few recognizable studies in COVID-19 diagnosis to show the importance of deep learning and chest X-ray images.

In the past few days, an experiment was completed by the use of two X-ray image datasets: the Adrain Rosebrock dataset [22] and the X-ray database of COVID-19 [23], which comprises 123 images of X-ray. This study accomplished the highest accuracy of 90% with DenseNet201 and VGG19. Though for the limitation of a small data set the experiment suffers. Hamdan [24] proposed a new COVID-19 detection framework known as COVID-Net. Seven different deep learning models were used in the model as ResNetV2, VGG19, Xception, InceptionV3, MobileNetV2, DenseNet201, and InceptionResNetV2. In this study, the model used 50 X-ray images.

Narin [25] accomplished the normal and the COVID-19 cases by a binary classification using deep learning models. In this study, ResNet50 achieved the best accuracy of 96%. Sethy et al. [26] developed a Deep Convolution Neural Network and obtained 83.5% accuracy by the model to classify the healthy and the COVID-19 positive cases. A deep learning-based ResNet model was proposed by Zhang [27] for the detection of COVID-19 applying Grand-CAM technology and finally, achieved 95.2% accuracy.

Wang [28] proposed the COVID-Net model for COVID-19 diagnosis using multiclass datasets (healthy, COVID-19, and pneumonia) and a pre-trained ImageNet model. This study used 13,975 X-ray images for the experiment among Resnet50, VGG19, and the developed model and achieved 93.3% accuracy [29-32].

Ozturk [33] developed a deep learning-based DarkNet method for detecting COVID-19. In this model, two different datasets were used, namely, normal images of chest X-ray database [34] and the COVID-19 positive database [35] for both binary (500 normal, 125 COVID) and (500 normal, 124 COVID, and 500 pneumonia). Finally, the experiment obtained 95.08% accuracy. Afshar et al. [36] developed a CNN-based COVID-CAPS model and got 95.7% accuracy. For the experiment, two different datasets were used for better performance [37].

Correspondingly, Oh et al. [38] used a pre-trained ResNet18 model to detect COVID-19. The model achieved 88.9% accuracy and different datasets were used as the USNLM dataset [39], CoronaHack [40], and the Japanese Society of Radiological Technology (JSTR) [41, 42].

3. Dataset Description

In this section, how we collected data, how we prepared the dataset is described in different subsections.

3.1. Data collection

For our work, we used chest X-ray images to predict COVID-19 positive or negative. The images used were taken from different open-source platforms and research papers. In this work, we used a total number of 2600 chest X-ray images both normal and COVID positive without image augmentation. The details of the images taken from open-source are written below –

a. We collected a total 100 of COVID affected X-ray images from Github which is published by Dr. Joseph Cohen [43]. Also, 250 healthy people's images were collected from Kaggle's Chest X-Ray dataset [44].
b. Furthermore, we collected 50 images of positive COVID-19 from the chest X-ray dataset of COVID-19 [45].
c. A total number of 480 images of COVID19^{++} X-ray and 438 images of healthy patient's chest X-ray were collected from the BIMCV database [46, 47].
d. Additionally, we obtained 290 images of COVID-19 positive chest X-ray from Cohen's dataset [35].
e. From the Actualmed COVID-19 chest X-ray dataset, we selected 180 images of COVID-affected patients [31].
f. Finally, we collected 200 COVID-19^{++} and 612 healthy category chest X-ray images from the database of COVID-19 radiography [32].

3.2. Dataset creation

We collected images of chest X-ray of both normal people and COVID-19 affected people from various sources but there are various issues with these images, namely incorrect labels, noisy, and duplicate. To clean these corrupt images we used NumPy and OpenCV and installed these packages in the Python working environment. After cleaning data, we developed our dataset for this work and separated the data into two different classes i.e. Normal and COVID-19^{++}.

Table 1 indicates the total number of chest X-ray images in the dataset used as training, validation, and testing. At the same time, the number of images used as COVID-19^{++} and Normal in the dataset is shown in (Fig. 1). In this study, the distribution of the dataset is used to reduce the imbalance data issue. The specimen of normal and COVID-19^{++} images in the dataset is shown in (Fig. 2).

Table 1 The total number of chest X-ray images per classification use for training, validation, and testing phases.

Category	Normal	COVID-19++
Training phase	**910**	**910**
Validation phase	**130**	**130**
Testing phase	**260**	**260**

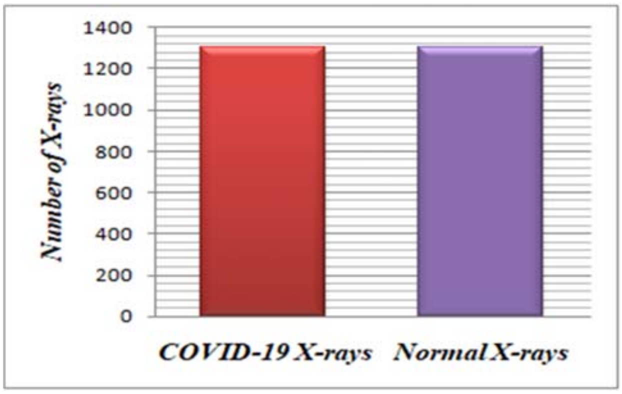

Fig. 1 The number of chest images used as COVID-19++ and Normal in the dataset.

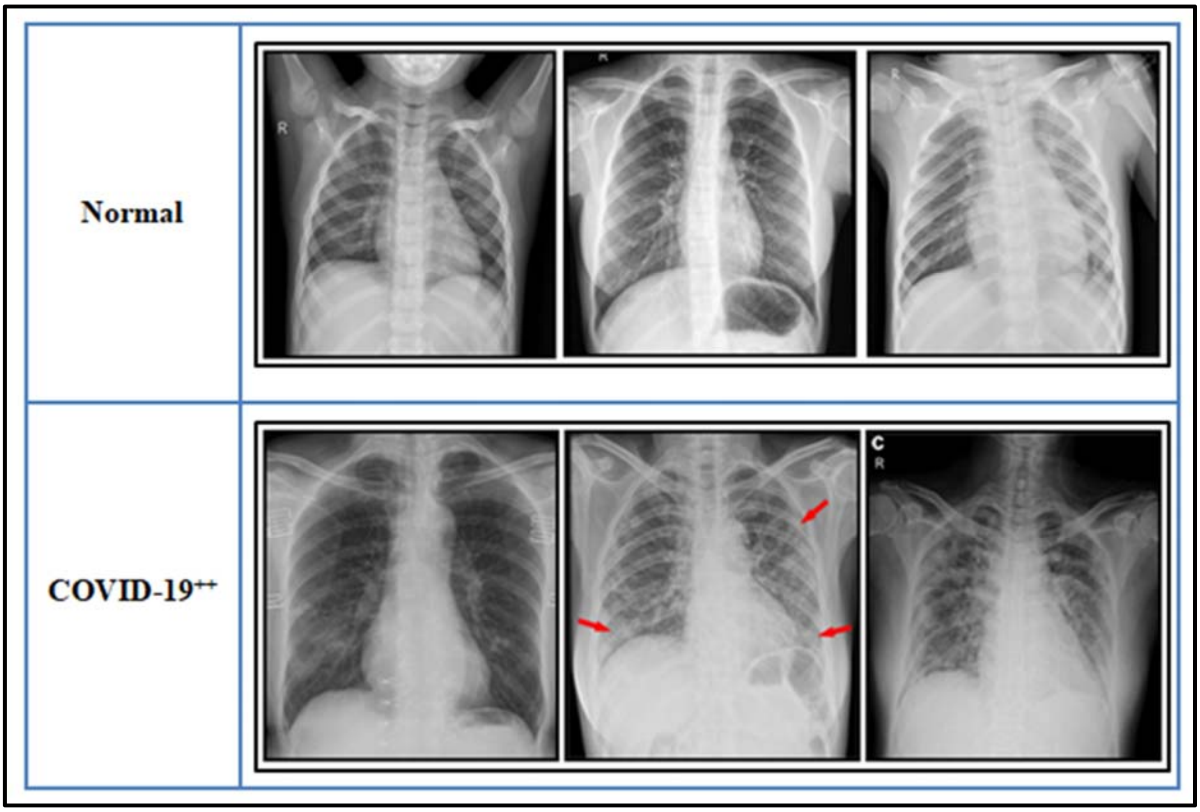

Fig. 2 The sample of chest X-ray images.

4. Proposed Methodology

At first, we developed an automated COVID-19 detection model by the use of Modified Convolutional Neural Network (CNN) architecture. Then we trained the model with the features representation mode of transfer-learning. This chapter provides detailed information about the proposed algorithm, preprocessing, augmentation of image, the proposed deep neural network and transfer-learning model and gives detailed information on the necessary settings for the model such as fine-tuning, experimental setup, and model evaluation stages. Fig. 3

contains the flowchart of our proposed COVID-19 classification methodology.

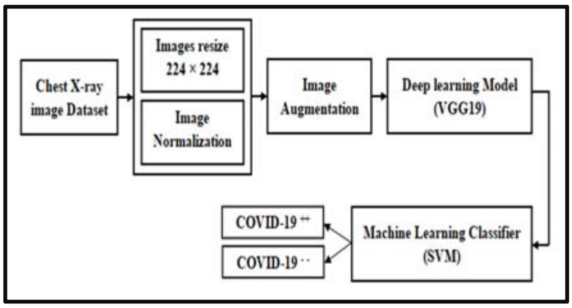

Fig. 3 Flowchart of our proposed COVID-19 classification methodology

4.1. Proposed Algorithm

The approaches used for developing the proposed method are given below –

Step 1:- Image preprocessing (resize, normalization, and augmentation).
Step 2:- Apply the images as the input of the deep learning-based VGG19 model.
Step 3:- Freeze convolutional block_1 and convolutional block_2.
Step 4:- Fetch the output of the last convolutional block.
Step 5:- Apply fully connected layers to the output.
Step 6:- Freeze fully connected layer.
Experiment_1: Freeze FC_3 layer.
Experiment_2: Freeze FC_1 layer.
Experiment_3: Freeze FC_2 layer.
Step 7:- Apply Activation map (ReLU).
Step 8:- Apply SVM for classification.

4.2. Preprocessing: image resize and normalization

Image resize and normalization techniques are applied in the preprocessing step to minimize the massive diversity of the original images.

At first, we converted all chest X-ray images to grayscale because the images were collected from different open-sources. Then every image is resized to 224 × 224 pixels to minimize experiment time. Finally, depending on radiation and the acquirement sources [48, 49], we applied the image normalization process to represent the enormous fluctuation of the image outlook (Contrast and brightness). This process scales and normalizes the pixel intensities to a range of [0, 255].

4.3. Augmentation of Image

A large number of data are needed to develop generalized and powerful deep learning-based models. Moreover, clinical imaging information and data are rare, for this reason, labeling the dataset is costly. To alleviate the problem of model overfitting different image augmentation techniques are applied [50] on the dataset such as width shift (a range of 20%), random rotation (a range of a maximum of 15 degrees), height shift (a range of 20%), and zoom (a range of 20%).

4.4. Deep Neural Networks and Transfer-learning

Machine learning has different fields; deep learning technology is one of them. The developed deep-learning technique is used to improve the task of image classification. A large number of train datasets are required for training the deep neural network model. In the platform of Python, we used Keras, OpenCV, PyTorch, TensorFlow, and Scikit-learn libraries for creating different structures of the model.

Feature extraction and parameter tuning are the two steps for accomplishing the transfer-learning technique. In the feature extraction step, it shows that the CNN-based pre-trained model uses the training data to contain new features from the given dataset. Feature extraction in transfer-learning is done by the defined dataset to solve the tasks of the CNN model. In the second step, parameter tuning is used to increase the performance by recreating and updating the model structure.

The pre-trained model used in this study is discussed below –

A deep convolutional neural network (CNN) based VGG19 model and machine learning classifier SVM are used to classify the images into two categories i.e. COVID-19^{++} or normal. To train the VGG19 model we used the images of chest X-ray.

VGG19: In 2014, VGG was first introduced and it is also acquainted as a deep convolutional neural network. VGG has multiple layers and is the advanced version of AlexNet. The multiple layers expand the model performance [51]. The main benefit of the VGG model uses only 3 × 3 convolutional layers. The model has another three fully connected layers. VGG19 is the sub-branch of the VGG network and provides around 143 million parameters for the work of the network and the model has 19 layers. Moreover, the model is used to explore the object of the images of chest X-ray. We used the VGG19 model and machine learning classifier SVM for the detection of COVID-19. Fig. 4 shows the VGG19 model architecture with 5 convolution blocks, 5 max-pooling and 3 FCN layers.

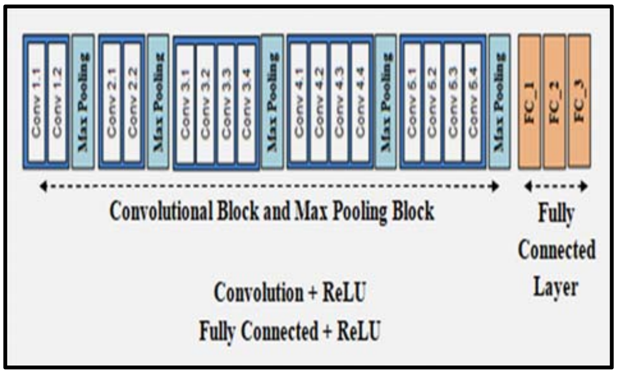

Fig. 4 Deep learning-based pre-trained VGG19 model

4.5. Fine-tuning

At first, we remove the common low-level sampling by freezing the weights of the initial layers of the model; the first few layers acquire knowledge of generic functionalities that generalize the images. The actual target of fine-tuning is to modify the recently collected chest X-ray dataset with these features.

In this stage, we tried to train several layers on the upper level of the base model. It is difficult to improve the pre-trained model's weights during the training period. In this situation, a new network head is attached with the intended categories and prepared for adjusting the weights as indicated by new patterns. We used the fine-tuning technique of the upper levels to improve the performance of the pre-trained model.

4.6. Experimental Setup

In our experiment, we used a deep learning-based model and trained the model by the programming language of Python. In offline, we trained the model on a Google Colaboratory server with Windows 10 operating system with Intel(R) Core™ i5-4200M CPU @ 2.50GHz. We installed TensorFlow 2.0 and Keras (along with the libraries of matplotlib, OpenCV, and scikit-learn) in our working environment. We used Adam optimizer to train the VGG19 model with the initialization weights. The rotation_range, learning rate, batch size and epoch number were set to 15, 1e-3, 12, and 50, respectively for the experiment. To overcome the model over-fitting problem a five-fold cross-validation method is used.

4.7. Model Evaluation

The following five criteria are used to calculate the performance of the model: Accuracy, Sensitivity, specificity, precision, and F1-score.

Accuracy = 100 × ((TP + TN) / (TP + TN + FP + FN))
Sensitivity = 100 × (TP / (TP + FN))
Specificity = 100 × (TN / (TN + FP))
Precision = 100 × (TP / (TP + FP))
F1-Score = 100 × (2 × ((Precision × Sensitivity) / (Precision + Sensitivity)))

Here, TP = True Positive, FP = False Positive, TN = True Negative, and FN = False Negative. In the COVID-19 dataset and model, True Positive is the ratio of COVID positive; False Positive is the ratio of COVID negative that is mislabeled as COVID positive; True Negative is the ratio of Covid negative that is exactly labeled as normal and False Negative is the ratio of COVID positive that is mislabeled as COVID negative.

5. Result and Discussion

In this part, we discussed the performance of the model, analyzed the achieved result.

5.1. Result Evaluation

We used chest X-ray images to detect COVID-19 affected people. We trained and tested the popular CNN-based VGG19 model by the images. We performed three experiments to achieve better accuracy in a short time by freezing Convolutional block_1 and Convolutional block_2 and also freezing fully connected layers. We show the achieved results from three experiments are given below –

Experiment No_1:

In our first experiment, we freeze the first two convolutional blocks and pooling layers. We also freeze fully connected layer 3 (FC_3). We use Convolutional block_3, Convolutional block_4, Convolutional block_5 and fully connected layer 1 (FC_1) and fully connected layer 2 (FC_2) of VGG19 for completing our experiment. The training phase has been completed up to the 50th epoch to remove the over-fitting problem in our Keras and Tensorflow model. We achieved 95.83% accuracy from our first experiment. Table 2 contains the performance of the prediction results achieved from the VGG19 model by freezing blocks and layers. Fig. 5 presents the training accuracy and the loss values of the model.

Table 2 Accuracy, Sensitivity, Specificity, Precision, F1-score of the experiment_1 are reported.

Experiment_1	Model	Performance Results				
		Accuracy	**Sensitivity**	**Specificity**	**Precision**	**F1-score**
	VGG19	95.83%	100%	91.67%	97.50%	98.73%

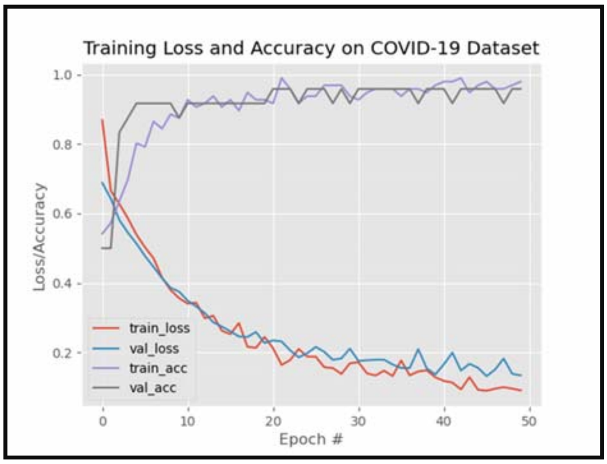

Fig. 5 Training curves for the loss and accuracy values.

Experiment No_2:

In our second experiment, we freeze the first two convolutional blocks and pooling layers. We also freeze fully connected layer 1 (FC_1). We use Convolutional block_3, Convolutional block_4, Convolutional block_5 and fully connected layer 2 (FC_2) and fully connected layer 3 (FC_3) of VGG19 for completing our experiment. The training phase has been completed up to the 50th epoch to remove the over-fitting problem in our Keras and Tensorflow model. We achieved 96.67% accuracy from our second experiment. Table 3 contains the performance of the prediction results achieved from the VGG19 model by freezing blocks and layers. Fig. 6 presents the training accuracy and the loss values of the model.

Table 3 Accuracy, Sensitivity, Specificity, Precision, F1-score of the experiment_2 are reported.

Experiment_2	Model	Performance Results				
		Accuracy	**Sensitivity**	**Specificity**	**Precision**	**F1-score**
	VGG19	96.67%	100%	93.33%	98%	98.99%

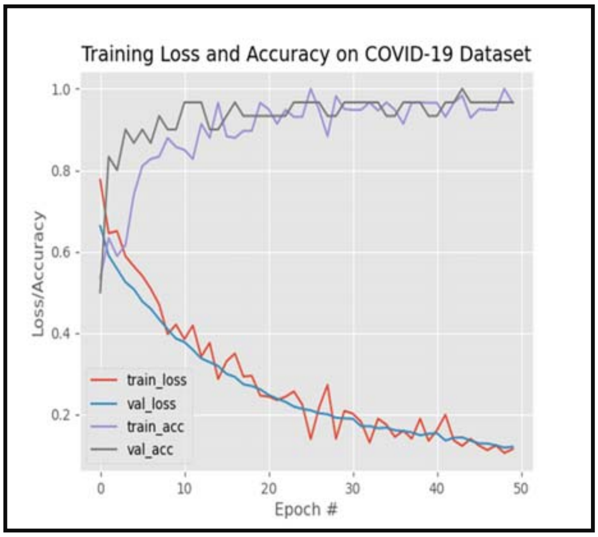

Fig. 6 Training curves for the loss and accuracy values.

Experiment No_3:

In our third experiment, we freeze the first two convolutional blocks and pooling layers. We also freeze fully connected layer 2 (FC_2). We use Convolutional block_3, Convolutional block_4, Convolutional block_5 and fully connected layer 1 (FC_1) and fully connected layer 3 (FC_3) of VGG19 for completing our experiment. The training phase has been completed up to the 50th epoch to remove the over-fitting problem in our Keras and Tensorflow model. We achieved 98.1% accuracy from our third experiment. Table 4 contains the performance of the prediction results achieved from the VGG19 model by freezing blocks and layers. Fig. 7 presents the training accuracy and the loss values of the model.

Table 4 Accuracy, Sensitivity, Specificity, Precision, F1-score of the experiment_3 are reported.

Experiment_3	Model	Performance Results				
		Accuracy	Sensitivity	Specificity	Precision	F1-score
	VGG19	98.10%	100%	95%	98.70%	99.34%

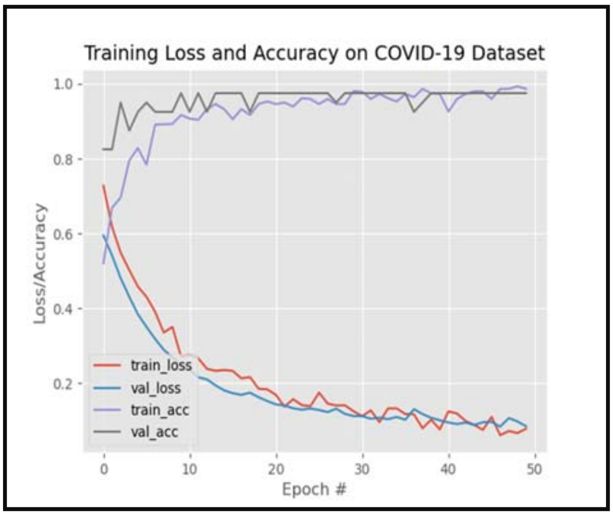

Fig. 7 Training curves for the loss and accuracy values.

The main advantages of this study are:

1. The experiment isn't affected by the imbalanced data.
2. Data augmentation was applied to improve the performance of the proposed model.
3. For the experiment, a large number of chest X-ray images are used.
4. The proposed method reduces the time complexity.

The study has some limitations:

1. For better working performance, we need high-quality equipment.
2. Combination of machine learning and deep features are only validated on normal vs. Covid-19 classification task.
3. Used dataset is not enough for a better result. Need to use the more different dataset for classification.

6. Conclusion

Early detection and prediction of COVID-19 play an essential role for the patients to minimize financial costs and the doctors to reduce the diagnostic time. Deep learning and Artificial intelligence are suitable for identifying images for the tasks taught. To protect the spread of the virus from COVID-19 affected people to others, early detection of the affected people plays a vital role. In this experiment, we proposed a CNN-based pre-trained VGG19 model to detect automatically COVID-19 affected people by the use of chest X-ray images. We performed three experiments and got the highest accuracy in experiment_3. Using a five-fold cross-validation process, in experiment_3 deep learning-based pre-trained VGG19 model achieved 98.10% accuracy, 100% sensitivity, 95% specificity, 98.70% precision, and 99.34% F1-score. We compared our study with other studies, the accuracy level of our model is better than other models. From this study, we believe that it will help the doctor and specialists to take decisions and reduce time in medical practice for the high performance of the model. In the early stage to detect COVID-19, this study will help to learn how to use deep transfer learning methods. In the future, through this study, we can easily train the metadata models by the mixed images, if different metadata and medical notes are provided for intubation. These metadata models will help us to predict severity and prognostic, and be highly applicable for patient management, risk stratification, and personalized care planning other critical pandemic situations. In future, we use our proposed method to perform different diseases classification task i.e. COVID-19^{++} vs. viral pneumonia vs. bacterial pneumonia vs. normal, Non-severe people vs. severe people.

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