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COV-VGX: An automated COVID-19 detection system using X-ray images and transfer learning

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ABSTRACT

Coronavirus (COVID-19) has been one of the most dangerous and acute deadly diseases across the world recently. Researchers are trying to develop automated and feasible COVID-19 detection systems with the help of deep neural networks, machine learning techniques, etc. In this paper, a deep learning-based COVID-19 detection system called COV-VGX is proposed that contributes to detecting coronavirus disease automatically using chest X-ray images. The system introduces two types of classifiers, namely, a multiclass classifier that automatically predicts coronavirus, pneumonia, and normal classes and a binary classifier that predicts coronavirus and pneumonia classes. Using transfer learning, a deep CNN model is proposed to extract distinct and high-level features from X-ray images in collaboration with the pretrained model VGG-16. Despite the limitation of the COVID-19 dataset, the model is evaluated with sufficient COVID-19 images. Extensive experiments for multiclass classifier have achieved 98.91% accuracy, 97.31% precision, 99.50% recall, 98.39% F1-score, while 99.37% accuracy, 98.76% precision, 100% recall, 99.38% F1-score for binary classifier. The proposed system can contribute a lot in diagnosing COVID-19 effectively in the medical field.

1. Introduction

Coronavirus infection 2019 is a respiratory disease brought about by a novel coronavirus called the severe acute respiratory syndrome Coronavirus-2. The first instance of COVID-19 was distinguished in Wuhan City, China [1]. The WHO proclaimed the COVID-19 as a public health emergency of international concern on January 30, 2020 [2]. The entire world is battling with more than 14.78 million influenced cases. A total of almost 3,124,726 death cases have been enrolled as of now [3]. Diagnosis systems for COVID-19 are time-consuming, and people are spreading the virus without even realizing they are already affected.

Starting with fever and dry cough, COVID-19 gradually results in deadly pneumonia, affecting the whole lungs of a patient. COVID-19 is different than a common virus or bacterial pneumonia [4]. The common cause of bacterial pneumonia is the *Streptococcus pneumoniae* (pneumococcus) [5]. Viral pneumonia is also caused by the virus, but COVID-19 pneumonia spreads in the lungs rapidly, extensively damaging the lung cells [6–8]. Thus, an accurate testing method is in dire need as failure to detect people with COVID-19 may delay treatment, hence increases the danger of spreading COVID-19 infection to others. As of this date, real-time reverse transcription-polymerase chain reaction (rRT-PCR) testing is the better testing method to distinguish coronavirus [9]. RT-PCR can identify CoV-2 RNA through respiratory samples (nasopharyngeal or oropharyngeal swabs). However, the sensibility of RT-PCR testing is eclipsed by the restricted accessibility of the test kit and the time needed for the result of this test, which usually takes a few hours to a day or two [10].

Many researchers have tried to develop an alternative method of rRT-PCR, such as experiments with radiological images. Their analysis shows that chest X-ray and CT data of COVID-19-infected patients have unique characteristics like ground-glass opacity. However, manual exploration of these radiological images is very time-consuming. Scientists have integrated deep learning techniques for the detection of COVID-19 using these images [11,12]. The machine learning techniques are currently assisting the medical sector in medical decision support systems, finding disease patterns, disease detection, etc. [13–15]. Therefore, COVID-19 detection using deep learning can provide higher accuracy in the shortest amount of time [16,17].

However, some limitations are still found in this system. First, the insufficiency of COVID-19-infected dataset to train the deep learning

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models. Without enough data, the trained model may perform worse like increasing the false-negative results (e.g., misclassification of COVID-19 cases as no-findings). Hence, more data and better systems are necessary for the prevention of COVID-19. Second, most of the systems only classify normal and COVID-19 cases. As the symptoms of normal pneumonia and COVID-19 are almost the same, distinguishing between pneumonia and COVID-19 is extremely important. This paper aims to increase the accuracy of automatic COVID-19 detection where existing works show lower accuracy due to lack of sufficient dataset.

In this paper, an automated system called COV-VGX is developed to detect COVID-19 from X-ray images. The system has developed two types of classifiers: a multiclass classifier that classifies COVID-19, pneumonia, and normal class label and a binary classifier that predicts COVID-19 and pneumonia-infected patients. As COVID-19 and pneumonia have almost the same symptoms, both classifiers are needed for the automatic detection of the disease.

The contributions of the paper are as follow:

i) The system's dataset contained 2000 COVID-19 infected X-ray images to train the CNN model.
ii) The system showed 98.92% accuracy, 97.31% precision, 99.50% recall, and 98.39% F1-score for multiclass classifier.
iii) COV-VGX has achieved 99.37% accuracy, 98.76% precision, 100% recall, and 99.38% F1-score for binary classifier.

The paper is organized as follows. Section 2 presents recent research for the detection of COVID-19 using X-ray images. Section 3 describes dataset description, proposed methodology, and proposed CNN model. Section 4 discusses the results and performance evaluation of COV-VGX. Finally, Section 5 presents the conclusion of the paper.

2. Related work

From the start of this pandemic, researchers have been trying their best to find the alternate solution of rRT-PCR to control this outbreak, such as working on machine learning or deep neural network-based systems utilizing X-ray or CT images. In the section, recent studies related to deep learning-based works using X-ray images are presented in a nutshell. Table 1 represents the brief description of related COVID-19 detection studies.

Waheed et al. [18] developed a new deep CNN system called CovidGAN for the detection of coronavirus using X-ray images. First, a GAN network called ACGAN was developed to produce chest X-ray images as a part of data augmentation. The synthetic images produced from CovidGAN promoted CNN's performance. Though the proposed CNN demonstrated 85% accuracy, the accuracy was increased to 95% by accumulating chest X-ray images produced by COVIDGAN. Thus, the performance of the CNN model was improved. Degadwala et al. [19] proposed FT-CNN model that performed well on detecting COVID-19 using chest X-rays images. The system utilized a fine-tuned CNN plan on image datasets to detect two types of classes, namely, normal and COVID-19. Using a transfer learning, the system FT-CNN achieved 90.70% accuracy and 70.32% precision. Toraman et al. [20] introduced a neural network-based system, Convolutional CapsNet, using chest X-ray images. Two types of classifiers are developed: one is a binary classifier that predicts between coronavirus and no-findings classes, and the other one is a multiclass classifier that decides coronavirus, no-finding, and pneumonia class labels. Binary classifier brought 97.24% accuracy where multiclass classifier resulted in 84.22% accuracy. Ozturk et al. [21] developed a deep CNN model called DarkNet for the detection of coronavirus using chest X-ray images. DarkNet was used for the YOLO object detection system. Seventeen convolutional layers and several kernels on each layer were introduced in the model. The system showed 98.08% accuracy for the binary classifier (coronavirus vs. normal) and 87.02% for multiclass classifier (coronavirus vs. normal vs. pneumonia).

Table 1
Brief description of related COVID-19 detection studies.

Author	Chest x-ray Dataset	Model	Performance
Waheed et al. [18]	Coronavirus = 403 Normal = 721	CovidGAN	95% accuracy
Sheshang Degadwala [19]	Coronavirus = 1200 Normal = 1341	FT-CNN	90.70% accuracy
Toraman et al. [20]	Coronavirus = 231 Pneumonia = 1050 Normal = 1050	Convolutional CapsNet	84.22% accuracy
Ozturk et al. [21]	Coronavirus = 127 Normal = 500 Pneumonia = 500	DarkNet	87.02% accuracy
Apostolopoulos et al. [22]	First Dataset: Coronavirus = 224 Normal = 700 Pneumonia = 504 Second Dataset: Coronavirus = 224 Normal = 714 Pneumonia = 504	MobileNet v2	96.78% accuracy
Junfeng Li [23]	Coronavirus = 1197 Normal = 10,192 Pneumonia = 7399	COVID-GATNet	94.30% accuracy
Alqudah et al. [24]	Coronavirus = 48 Normal = 23	AOCT-Net	95.2% accuracy
Sahinbas et al. [25]	Coronavirus = 70 Normal = 70	VGG16	80% accuracy

Apostolopoulos et al. [22] introduced several deep learning-based pretrained models for the detection of coronavirus disease using transfer learning. The pretrained models included VGG-19, Inception, Inception ResNet v2, MobileNet v2, and Xception. The system consisted of two types of datasets. The best accuracy, recall, and specificity by the system were 96.78%, 98.66%, and 96.46%, respectively. Li, Junfeng, et al. [23] proposed a new neural network model called COVID-GATNet, for the detection of the COVID-19 using chest X-ray images. COVID-GATNet was used to detect three types of classes, namely, COVID-19, pneumonia, and normal patients. The system showed 94.30% accuracy with more than 95% precision, and F-1 score was used to detect COVID-19 positive cases. Alqudah et al. [24] introduced artificial intelligence-based hybrid models to predict coronavirus using X-ray images and introduced CNN model AOCT-Net for feature extraction. Several machine learning algorithms (random forest and support vector machine) were applied to predict coronavirus and no-findings. The dataset was increased to 912 X-ray images during the application of data augmentation. After the feature extraction using CNN, the system achieved 95.2% accuracy for the softmax classifier, 90.5% accuracy for the SVM classifier, and 81% accuracy for the RF classifier. Sahinbas et al. [25] introduced several deep learning-based pretrained models for the detection of coronavirus disease using transfer learning. The models included InceptionV3, ResNet, VGG16, VGG19, and DenseNet. Among the pretrained models, VGG-16 performed the best with 80% accuracy.

3. Proposed methodology

The proposed system COV-VGX extracts distinct features from chest X-ray images and develops two types of classifiers to predict coronavirus disease such as an automatic coronavirus detection multiclass classifier which takes an image and predicts whether the X-ray image is COVID-19 or pneumonia infected, normal cases, or not. Hence, the system proposes a binary classifier that decides between COVID-19 and pneumonia cases. After collecting the dataset from different sources, the dataset is pre-processed. Using transfer learning, pretrained model VGG-16 is trained for the model evaluation. Few new layers are added with the base model to avoid the overfitting problem of training the model. Finally, the classifiers are evaluated through precision, recall, accuracy, F1-score, and ROC curve. Fig. 1 shows the architecture of COV-VGX.

3.1. Description of datasets

Many available datasets of X-ray images from normal people and pneumonia infection cases are identified. However, COVID-19 infected X-ray images are not readily available. The dataset of COVID-19 infected patient's X-ray was collected from sources like Github repositories [26, 27] and SIRM database [28]. Pneumonia and normal X-ray image dataset was collected from the Kaggle repository [29]. Fig. 2 shows some sample images of these three classes. The dataset is prepared with 6000 X-ray images. Of which, 2000 are for COVID-19 infected cases, 2000 are for pneumonia cases, and 2000 are for normal cases. A total of 70% images are selected as training set, 10% images as a validation set, and 20% images as the test set. A total of 1400 x-ray images are used for training, 200 for validation, and 400 for testing each category. Table 2 describes the class-wise dataset size and partition.

3.2. Data preprocessing

As the dataset is obtained from multiple sources, images of different sizes are observed. Hence, data preprocessing is performed. The input image of every image is resized to 124 × 124 pixels. Thereafter, data augmentation is performed on the dataset to reduce the overfitting problem. Image data augmentation is utilized to increase the size of the dataset by making altered forms of pictures. Data augmentation helped the proposed model to perform better with exceptional features of the training images. The Keras deep learning library was used for information expansion. The data is augmented by applying four geometric transformations:

- Height shift range argument to translate image horizontally
- Width shift range argument to translate image vertically
- Shear range argument for applying the shearing transformation
- Zoom range argument for randomly zooming inside pictures

3.3. Convolutional neural network (VGG-16)

Several pretrained CNN models exist like LeNet, AlexNet, VGG-16, GoogLeNet, ResNet, etc. COV-VGX selected VGG-16 for evaluation because of its deeper networks yet smaller filters. VGG-16 consists of 16 layers of CNN architecture which uses a filter of size 3 × 3 for all convolution layers, thus the smallest size filter. The input to the model is 224 x 224 size RGB images. The features of the image are extracted through a series of convolutional layers. The convolution stride is 1. The spatial padding of convolutional layer input must have a maintained spatial size after each convolution operation. Nonlinear activation is performed on convolution output. Spatial pooling is performed by five pooling layers. Max-pooling is performed with a 2 × 2 size filter and stride 2. After a series of convolutional layers and max-pooling layers, three fully connected layers (FCL) are created. The final layer is the softmax layer which classifies COVID-19, pneumonia, and normal cases. Fig. 3 shows the architecture of VGG-16.

3.4. Using transfer learning

Transfer learning is a method where a model trained for one classification problem is used in training for another classification problem. In deep learning, several pretrained models that are already trained on image-net dataset for 1000 classification systems are used to train another desired classification problem. Some new layers are added with the pretrained model and a new model is created to train the system. COV-VGX used a categorical cross-entropy loss function. Given that COV-VGX uses both multiclass classifier and binary classifier, categorical cross-entropy is well suited for the proposed system.

The desired portion of the pretrained VGG-16 without the fully connected output layers was integrated into the new proposed CNN model. The weights of the pretrained VGG-16 were frozen to prevent them from the update. Only new layers of the proposed model were trained without updating the weights of the VGG16 layers. After loading the VGG-16 model without the classifier part of the model, several new layers were added to the proposed CNN. Fig. 4 shows the architecture of the proposed CNN. First, the flattened layer was added to convert the 2D feature vector into a 1D feature map.

Second, FCL of 64 neurons was added to learn how to illustrate the extracted features on the new x-ray dataset. A dropout layer with a threshold of 0.5 was added to overcome the overfitting problem. Finally, FCL was added as an output layer. The output layer has three neurons when training the multiclass x-ray detection model or two neurons when training the binary classifier. Table 3 shows the model summary of the proposed CNN model.

3.5. Metrics for performance evaluation

To evaluate the performance of COV-VGX, several performance metrics are used. Both the multiclass and binary classifiers are evaluated

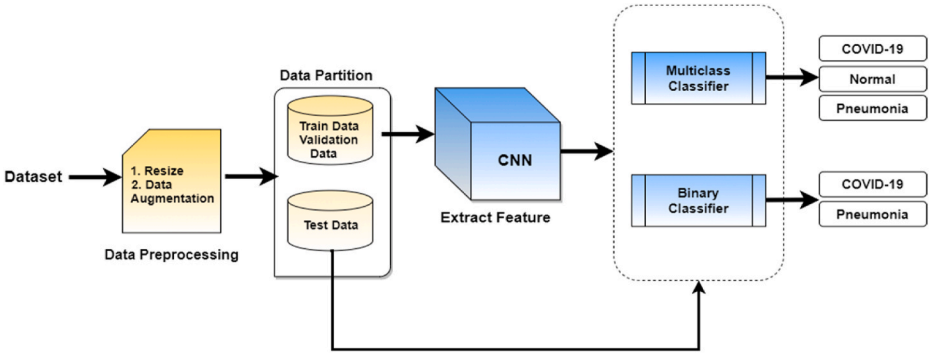

Fig. 1. Architecture of COV-VGX.

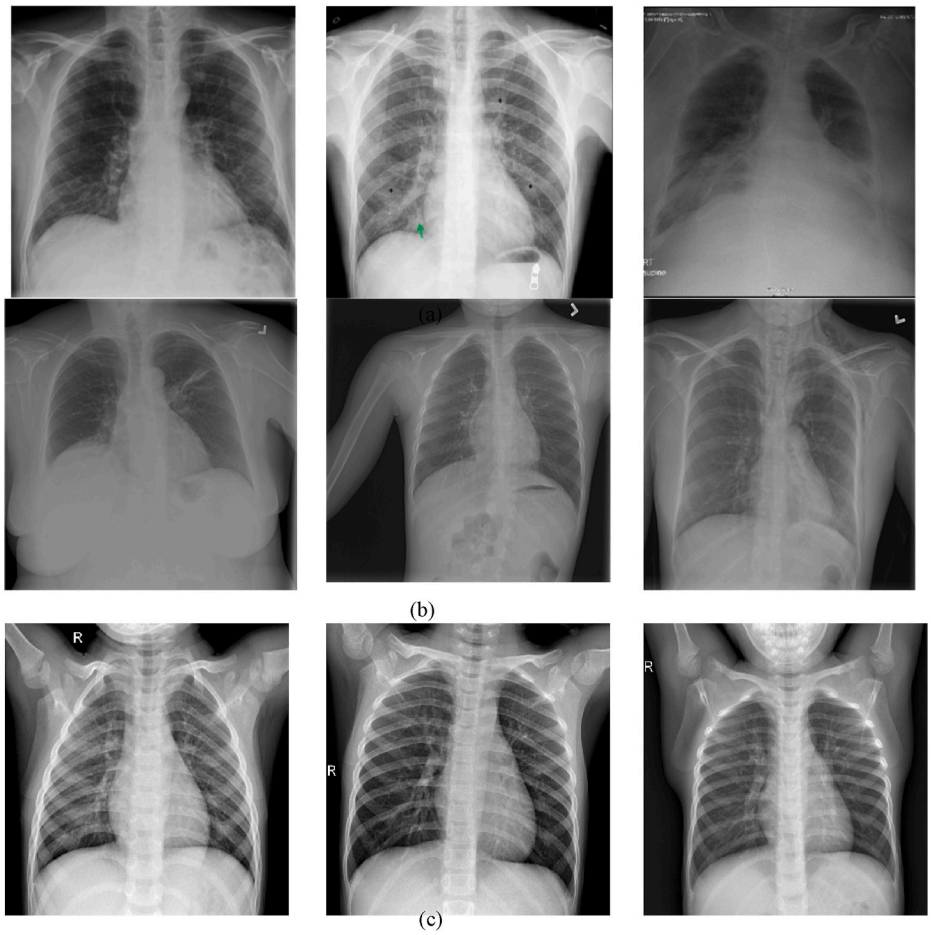

Fig. 2. X-ray images of (a) COVID-19, (b) pneumonia, and (c) normal cases.

Table 2
Class-wise dataset size and partition.

Partition	Coronavirus	Pneumonia	Normal	Total
Train	1400	1400	1400	4200
Validation	200	200	200	600
Testing	400	400	400	1200
Total	2000	2000	2000	6000

separately concerning accuracy, precision, recall, and F1-score. The metrics are evaluated separately for each class label. To evaluate these metrics, four basic terms are considered: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). When measuring the accuracy for COVID-19 class labels, TP is correctly classifying COVID-19 cases by multiclass or binary models. FP is incorrectly classifying normal or pneumonia cases as COVID-19 cases. TN is the number of correctly classifying normal or pneumonia cases. FN is incorrectly classifying coronavirus cases as normal or pneumonia cases. Similarly, when measuring the accuracy for pneumonia class labels, TP is correctly classifying pneumonia cases by multiclass or binary model;

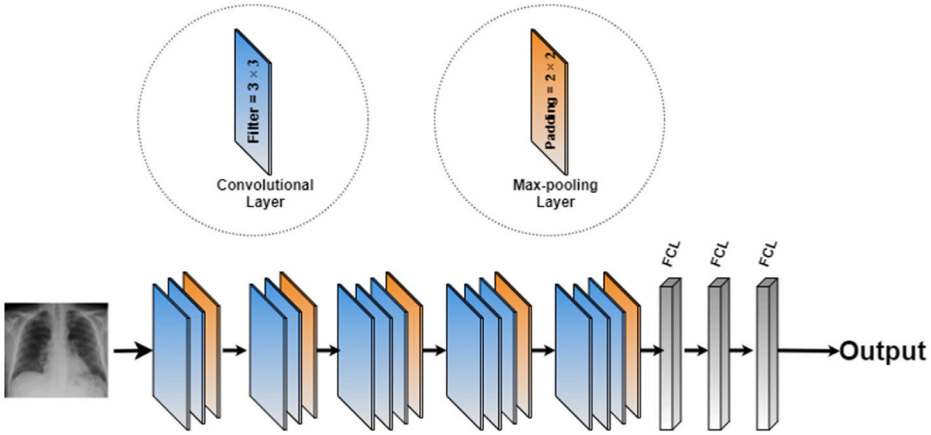

Fig. 3. VGG-16 architecture.

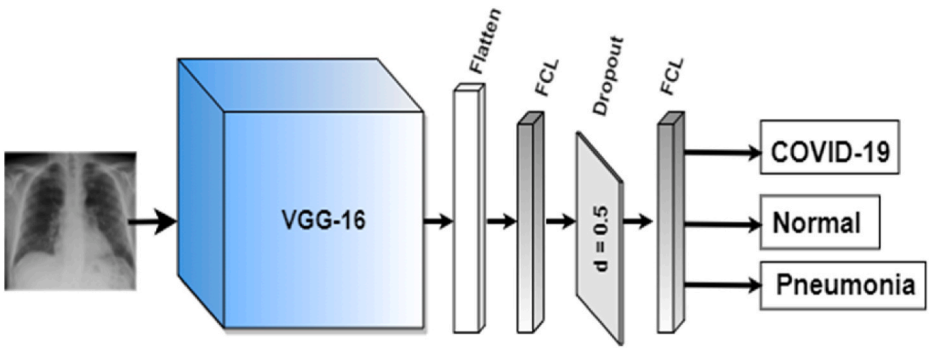

Fig. 4. The architecture of proposed CNN model. vector into a 1D feature map. Second, FCL of 64 neurons was.

Table 3
Model summary of the proposed CNN model.

Layer	Output Size	Parameters
Vgg16 (functional)	[7, 7, 512]	14714688
flatten (flatten)	[25088]	0
dense (dense)	[64]	1605696
dropout (dropout)	[64]	0
dense_1 (dense)	[3] (multiclass) [2] (binary)	195 (multiclass) 130 (binary)

FP is incorrectly classifying normal or COVID-19 cases as pneumonia cases, and so on.

4. Experimental analysis

COV-VGX trains multiclass and binary CNN models separately for feature extraction using x-ray images. The models are compiled with Adam optimizer. A batch size of 32 with 50 epochs is used for training data. Within 50 epochs, two models started saturating and showed expected accuracy. The epoch number is determined by ModelCheckpoint and EarlyStopping. Thus, performance is evaluated by accuracy, precision, recall, F1-score, and ROC curve. For binary classifier, training and testing times are 7993.4 s and 97.5 s, respectively. For multiclass classifier, training and testing times are 11749.1 s and 137.0 s, respectively.

4.1. Experimental setup

Two types of online notebook systems are used for evaluating the models, namely, Kaggle notebook and Google Colab. Python is used because of its conciseness and simplicity. The necessary libraries are TensorFlow and Keras version 2.4.0. Kaggle provided 9 h of sessions, 13 GB RAM, and 19.6 GB DISK. Google colab provided 12.72 GB RAM and 107.77 GB DISK. Google drive is used to import the dataset.

4.2. Analysis of the results

Fig. 5 presents the training and validation accuracy for the multiclass classifier.

Training accuracy and loss are 98.95% and 0.003, respectively. Validation accuracy and loss are 97.67% and 0.077, respectively. Similarly, Fig. 6 shows training and validation accuracies for binary classifier, where training accuracy and loss are 99.98% and 0.0005, respectively, while validation accuracy and loss are 98.75% and 0.0640, respectively.

Fig. 7(a) shows confusion metrics for the multiclass model. The dataset contained images of 400 coronavirus cases, 400 pneumonia cases, and 400 normal cases. Thus, the system correctly classifies 398 coronavirus cases and misclassifies two coronavirus cases as normal cases. COV-VGX correctly classifies 391 normal cases and misclassifies nine normal cases as COVID-19 cases. Besides, correctly classifying 398 pneumonia cases and misclassifying two pneumonia cases as COVID-19 cases. Fig. 7(b) shows confusion metrics for a binary classifier. The system correctly classifies all COVID-19 cases, but correctly classifies 395 pneumonia cases and misclassifies five pneumonia cases as COVID-19 cases.

Table 4 and Fig. 8 show the performance evaluation of COV-VGX for each class label of COVID-19, pneumonia, and normal cases. For COVID-19 cases, multiclass classifier shows accuracy of 98.91%, precision of 97.31%, recall of 99.50%, and F1-score of 98.39%. For normal cases, accuracy of 99.08%, precision of 99.49%, recall of 97.75%, and F1-score of 98.61%. For pneumonia cases, accuracy is 99.83%, precision is 100%, recall is 99.5%, and F1-score is 99.75%. For the binary classifier, accuracy is 100%,

precision is 98.77%, recall is 100%, and F1-score is 99.38% in the case of coronavirus class label. For pneumonia cases, accuracy is 98.75%, precision is 100%, recall is 98.75%, and F1-score is 97.37%. Table 5 also shows the overall performance evaluation of the binary classifier. The system achieved 99.37% accuracy, 98.76% precision, 100% recall, and 99.38% F1-score.

Fig. 9(a) represents the receiver operating characteristic (ROC)

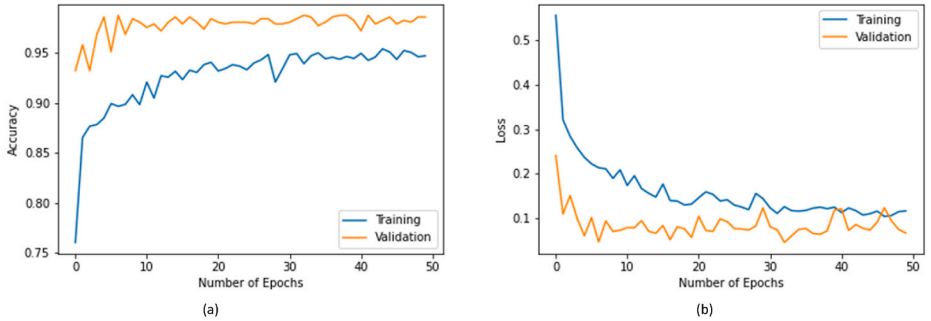

Fig. 5. Performance of the multiclass classifier of COV-VGX. (a) Training and validation accuracy and (b) Training and validation loss.

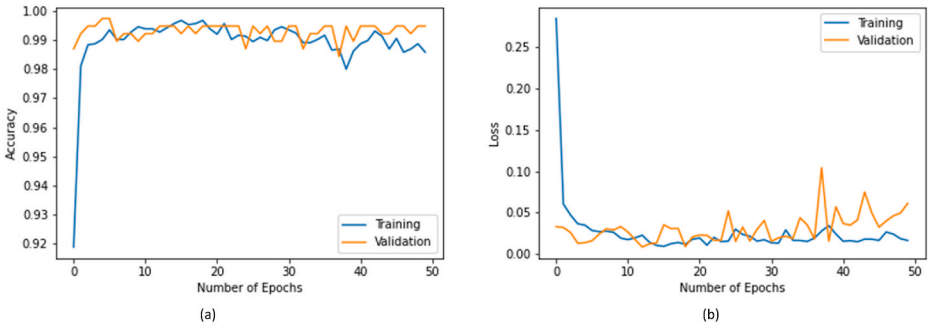

Fig. 6. Performance of the binary classifier of COV-VGX. (a) Training and validation accuracy and (b) Training and validation loss.

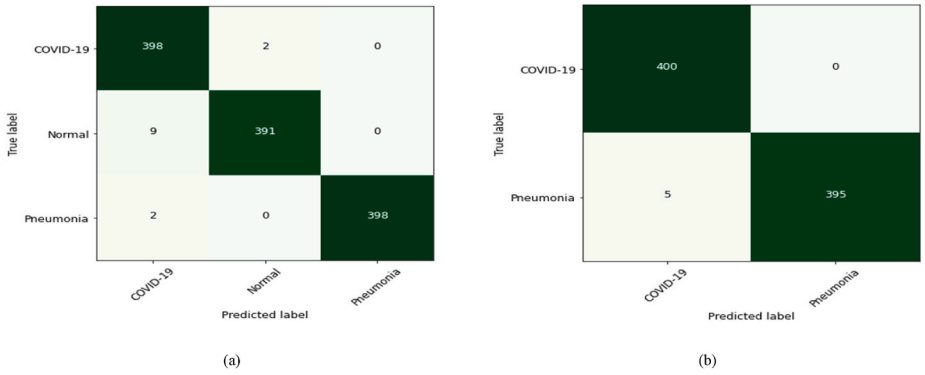

Fig. 7. Confusion matrix of two classifiers used in COV-VGX (a) Multiclass (b) Binary.

Table 4
Performance evaluation of multiclass and binary classifiers of COV-VGX.

Classifiers	Class	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Mulitclass	COVID	98.91	97.31	99.5	98.39
	Normal	99.08	99.49	97.75	98.61
	Pneumonia	99.83	100	99.5	99.75
Binary	COVID	100	98.77	100	99.38
	Pneumonia	98.75	100	98.75	97.37

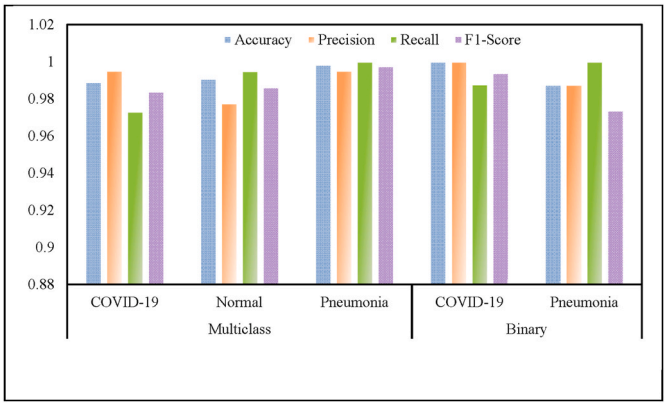

Fig. 8. Graphical representation of the classifiers used of COV-VGX.

Table 5
Performance evaluation of the binary classifiers used in COV-VGX.

Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
99.37	98.76	100	99.38

curve. for the multiclass classifier, where the COVID-19, normal, and pneumonia cases cover 98.53%, 99.19%, and 99.88% areas. Fig. 9(b) represents the ROC curve for the binary classifier, where COVID-19 and pneumonia cover 99.38% and 99.38% area.

5. Discussion

The comparative performance evaluation of COV-VGX with other recent studies is described in Table 6. The systems in Refs. [20,21] showed the accuracy of 84.22% and 87.02%, respectively. The systems in Refs. [22–24] increased the accuracy level to 96.78%, 94.30%, and 95.2%, respectively. COV-VGX demonstrated 98.92% accuracy for multiclass classifier and 99.37% accuracy for binary classifier which are higher than all other systems.

Based on the results, COV-VGX can significantly contribute to detect COVID-19. The strength of the system is that the model has been trained with enough datasets compared to recent research. The system can be used both as a binary and multiclass classifier. However, the weakness of the model is the inability to distinguish between viral and bacterial pneumonia images. Further research can be conducted to improve the model as an all-in-one detection system.

6. Conclusions

The world is facing a tremendous situation because of the COVID-19 pandemic. Millions of people are dying, and their families have been suffering a lot. COV-VGX can help the healthcare system by detecting COVID-19 automatically from X-ray images. The proposed COV-VGX extracts deep, unique, and high-level features from x-ray images and classifies them among COVID-19, pneumonia, and normal classes. Results shows 98.91% accuracy, 97.31% precision, 99.50% recall, and 98.39% F1-score for multiclass classifier; while 99.37% accuracy, 98.76% precision, 100% recall, and 99.38% F1-score for binary classifier. In the future, the system can be enhanced to detect COVID-19 not

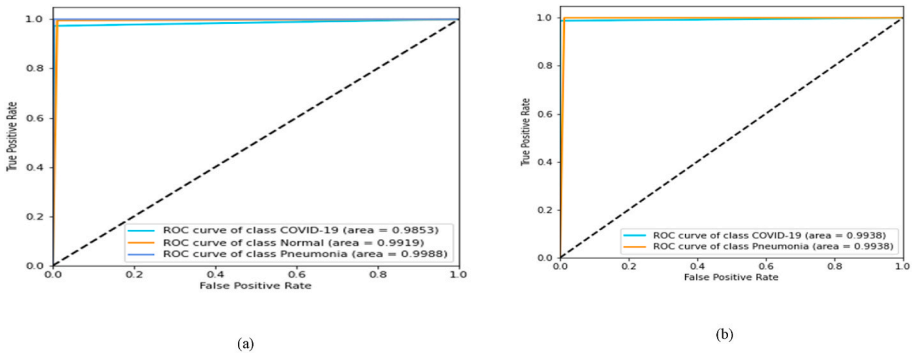

Fig. 9. ROC curve of the classifiers of COV-VGX.

Table 6
Performance comparison of COV-VGX with recent existing works.

Author	Chest X-ray Dataset	Accuracy
Waheed et al. [18]	Coronavirus = 403 Normal = 721	95%
Toraman et al. [20]	Coronavirus = 231 Pneumonia = 1050 Normal = 1050	84.22%
Ozturk et al. [21]	Coronavirus = 127 Normal = 500 Pneumonia = 500	87.02%
Apostolopoulos et al. [22]	First Dataset: Coronavirus = 224 Normal = 700 Pneumonia = 504 Second Dataset: Coronavirus = 224 Normal = 714 pneumonia = 504	96.78%
Junfeng Li [23]	Coronavirus = 1197 Normal = 10,192 Pneumonia = 7399	94.30%
Alqudah et al. [24]	COVID-19 = 48 Normal = 23	95.2%
COV-VGX	COVID-19 = 2000 Normal = 2000 Pneumonia = 2000	98.92% (multiclass) 99.37% (binary)

only from chest X-ray images but also from CT images and classify viral and bacterial pneumonia images as well.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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