Online-Journals.org

iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 19 No. 9 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v19i09.38147

PAPER

COV-CTX: A Deep Learning Approach to Detect COVID-19 from Lung CT and X-Ray Images

Muhammad Sheikh Sadi[1,2] (✉), Mohammed Alotaibi[3], Prottoy Saha[1], Fahamida Yeasmin Nishat[1], Jerin Tasnim[1], Tareq Alhmiedat[4], Hani Almoamari[5], Zaid Bassfar[3]

[1]Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh

[2]Institute of Information and Communication Technology, Bangladesh University of Engineering and Technology, Dhaka, Bangladesh

[3]Faculty of Computer & Information Technology, University of Tabuk, Tabuk, Saudi Arabia

[4]Industrial Innovation & Robotics Center, University of Tabuk, Tabuk, Saudi Arabia

[5]Faculty of Computer and Information Systems, Islamic University of Madinah, Medina, Saudi Arabia

sadi@cse.kuet.ac.bd

ABSTRACT

With the massive outbreak of coronavirus (COVID-19) disease, the demand for automatic and quick detection of COVID-19 has become a crucial challenge for scientists around the world. Many researchers are working on finding an automated and effective system for detecting COVID-19. They have found that computed tomography (CT-scan) and X-ray images of COVID-19 infected patients can provide more accurate and faster results. In this paper, an automated system is proposed named as COV-CTX which can detect COVID-19 from CT-scan and X-ray images. The system consists of three different CNN models: VGG16, VGG16-InceptionV3-ResNet50, and Francois CNN. The models are trained with CT-scan and X-ray images individually to classify COVID-19 and non-COVID patients. Finally, the results of the models are combined to develop a voting ensemble of classifiers to ensure more accurate and precise results. The three models are trained and validated with 9412 CT-scan images (4756 numbers of COVID positive and 4656 numbers of non-COVID images) and 3257 X-ray images (1647 numbers of COVID positive and 1610 numbers of non-COVID images). The proposed system, COV-CTX provides up to 96.37% accuracy, 96.71% precision, 96.02% F1-score, 97.24% sensitivity, 95.35% specificity, 92.68% Cohens Kappa score for CT-scan image based COVID-19 detection and 99.23% accuracy, 99.37% precision, 99.22% F1-score, 99.39% sensitivity, 99.07% specificity, 98.46% Cohens Kappa score for X-ray image based COVID-19 detection.

KEYWORDS

COVID-19, transfer learning, voting ensemble, CT-scan images, X-ray images

1 INTRODUCTION

At present, the most significant challenge that human beings are facing is controlling COVID-19. As the virus contains airborne properties, it is more likely to spread quickly due to its nature of the virus. It has become a global pandemic that has been spread across 217 countries, infecting more than 64.5 million people with a death case of 1.49 million [1]. The largest problem of this pandemic is that

Sadi, M.S., Alotaibi, M., Saha, P., Nishat, F.Y., Tasnim, J., Alhmiedat, T., Almoamari, H., Bassfar, Z. (2023). COV-CTX: A Deep Learning Approach to Detect COVID-19 from Lung CT and X-Ray Images. *International Journal of Online and Biomedical Engineering (iJOE)*, 19(9), pp. 47–65. https://doi.org/10.3991/ijoe.v19i09.38147

Article submitted 2023-01-17. Resubmitted 2023-02-22. Final acceptance 2023-03-17. Final version published as submitted by the authors.

it is spreading fast. The mainstream test kits are becoming unable to keep pace. Infected persons' sneeze, cough, surface contaminated with sneeze and cough are very harmful to any healthy person.

COVID-19 rarely shows any noticeable symptoms. Most of the changes caused in the lungs are very similar to pneumonia-based diseases. Hence, detection of COVID-19 from the lung CT-scan or X-ray images has become very tough. The systems must be more accurate to give the proper results. The number of false-negative cases may also increase due to a lack of efficient systems. The increase of false-negative instances is a very alarming situation. It increases the probability of roaming around and gathering people in social groups carrying the COVID-19 virus without even knowing [2]. It is one of the significant causes that fuel the spread of COVID-19. Also, the vaccination doesn't provide long-term immunity [3]. Thus, considering all these circumstances, developing a COVID-19 detection system with greater accuracy has become one of the most important challenges nowadays to overcome this outbreak.

From the beginning of COVID-19, scientists around the world are researching day and night to fight this unstoppable pandemic. The goal is to help people from getting infected and to cure the infected people. For this reason, researchers have never stopped looking for new and innovative solutions with the help of AI. However, early and fast diagnosis of COVID-19 is crucial in order to address the affected people's medical needs and to stop rapid spreading [4]. Both antigen and antibody tests require various toolkits and huge time requirements to fight the pace of mass spreading. Besides, the tests are not only expensive but also time-consuming. In most cases, it is too late to cure when the existence of a COVID-19 virus is identified. The issue needs to be solved at once to take part in saving billions of lives. Researchers worldwide are now more focused on finding out alternative ways to mitigate this problem.

Many researchers have proposed various artificial intelligence (AI) based systems to detect COVID-19. They have focused on image classification techniques to differentiate COVID-19 infected people from others (normal, viral, or bacterial pneumonia) by analyzing the image dataset of lung CT-scan and X-ray test reports [5, 6]. These AI and image analysis-based schemes can reduce the rate of incorrect COVID-19 diagnosis results. However, these are developed with a small amount of dataset due to the lack of sufficient CT-Scan or chest X-ray data of COVID-19 patients. As most COVID-19 patients rely on the antigen test, the collection of the required dataset for this research is not sufficient. The main strength of this paper is that the research explains two different classifier models based on a voting ensemble. Furthermore, the models were trained on large datasets. Finally, the models can generate results individually from CT-scan images or X-ray images.

The major objectives of this paper are as follows.

1) To develop an efficient model which can diagnose Covid-19 reliably and rapidly.
2) To develop a voting ensemble with three pre-trained models for improving the classification task.
3) To achieve better accuracy, precision, F1-score, sensitivity, and specificity for Covid-19 diagnosis based on CT-scan images, and X-ray images.
4) To collect and use voluminous benchmark datasets for training and testing purposes so that a reliable model can be generated.

The rest of the paper is summarized as follows. Section 2 represents a survey of related work on COVID-19 detection in recent times. Section 3 elaborates the proposed methodology of this paper. Section 4 provides a detailed analysis of the experiment. Section 5 concludes the paper.

2 RELATED WORK

A wide range of medical diagnoses has been used to detect corona-infected patients. Among all of them, the CT scan and X-ray images seem to show the most significant method for the detection of COVID-19. The research related to this area is shown as follows.

Mucahid et al. [7] used CT images to classify COVID-19 with the help of a deep learning network. The system detects three cases: COVID-19 cases, influenza, and healthy cases. The researchers classified them by a three-dimensional deep learning model. However, the model showed 87.6% accuracy.

The method proposed by Umut et al. [8] detected coronavirus disease from CT images. The system developed a feature fusion and ranking method. The research showed 96.54% Matthews Correlation Coefficient (MCC) metrics, 98.28% F1-score, and 98.27% accuracy. The research was evaluated with a very small dataset.

Arpan et al. [9] developed a system to test the coronavirus-infected patient from X-ray reports but did not have any feature to operate with CT-image results. The system classified the input image into three sections: Normal, (Bacterial/Viral) Pneumonia, and COVID-19.

Ali et al. [10] proposed an Artificial Intelligence-based system for faster detection of COVID-19 cases using X-ray images. The system developed a hybrid AI model. The hybrid models showed a better performance score with 95.2% of accuracy.

Taban et al. [11] introduced a new method to boost up the radiography-based diagnosis with the help of machine learning. The system used X-ray images to evaluate the CNN architecture. They proposed a CNN architecture called CNN-X for X-ray testing to get a better result. The model gained 97.82% accuracy.

Kevser et al. [12] introduced a deep learning-based system that worked on raw X-ray images and run five different pre-trained CNN architectures for the detection of COVID-19. They are VGG16, VGG19, ResNet, DenseNet, and InceptionV3. Among them, the VGG16 model showed higher accuracy of 80% to classify COVID-19 cases.

Xin He et al. [13] proposed a deep learning model to identify COVID-19 cases. The CT-scan images of patients were used as a data set to train two types of state-of-the-art deep learning models. The model gained 88.63% accuracy at the end of the experiment.

Saban et al. [14] introduced a system that classified the coronavirus disease from X-ray and CT images. The research classified the images into 6 different classes. It showed that the results of X-ray and CT images were the same for the initial and coronavirus case. Pneumonia or other cases varied in the result. The classification was done by SVM. The research showed 90% accuracy.

Zahangir et al. [15] introduced a new method to detect COVID-19 from X-ray images and CT scan images. The infected regions were identified and analyzed through the deep learning model with the detection and localization method. However, it showed 84.67% and 98.78% accuracy for X-ray and CT images respectively.

3 METHODOLOGY

This section is comprised of two sub-sections: dataset preparation, and COVID-19 classification strategy.

3.1 Dataset preparation

The three different pre-trained models are trained using available public CT-scan image data and X-ray image data individually. Images of COVID-19 infected and non-COVID cases are used to conduct the experiments. The dataset is divided into 80% training and 20% validation. Figure 1 represents a few examples of COVID-19 infected CT-scan images and non-COVID CT-scan images. A total of 4756 COVID-19 infected CT-Scan images are collected from IEEE-Dataport [16] developed by KaichaoWu. Non-COVID CT-scan data includes 2117 images from the Github repository developed by Mohammad Rahimzadeh [17], 1996 images from IEEE-Dataport [18] published by Tao Yan, and 543 images published by a Kaggle user named MOHAMED MERSET [19]. Total 4656 images of Non-COVID CT-scan images are collected from these sources. Thus, the system dataset contains a total of 9412 CT images. The dataset is partitioned into 80%:20%; a training set with 7531 CT images and a validation set with 1881 CT images. Then a total of 3257 chest X-ray images are collected from different sources. A total of 1647 COVID-19 infected X-ray images are collected for this research. Among these, 650 COVID-19 images are from the Github repository developed by Cohen et al [20], and the rest 997 COVID-19 images are collected from another Github source [21], SIRM database [22], TCIA [23], radiopaedia.org [24], and Mendeley [25]. The images of these repositories have been collected from different open sources, and hospitals. The non-COVID X-ray dataset consists of 1610 images which include 1050 images from the Kaggle repository [26] and 560 images from NIH chest X-ray images [27]. Figure 2 represents few examples of COVID-19 infected X-ray images and Non-COVID X-ray images. The dataset is partitioned as a training set with 2606 X-ray images and a validation set with 651 X-ray images. The division of the CT-scan and X-ray dataset are described in Table 1.

Table 1. Partition of the dataset into training and testing set

	CT-Scan			X-Ray		
	Training	Validation	Total	Training	Validation	Total
COVID-19	3832	924	4756	1318	329	1647
Non-COVID	3699	957	4656	1288	322	1610
Total	7531	1881	9412	2606	651	3257

For better performance, the models are needed to be trained with images of the same size. The dataset has a wide range of images with different shapes. Hence, all images are reshaped to 150x150 pixels. Then the image normalization is done for further implementation.

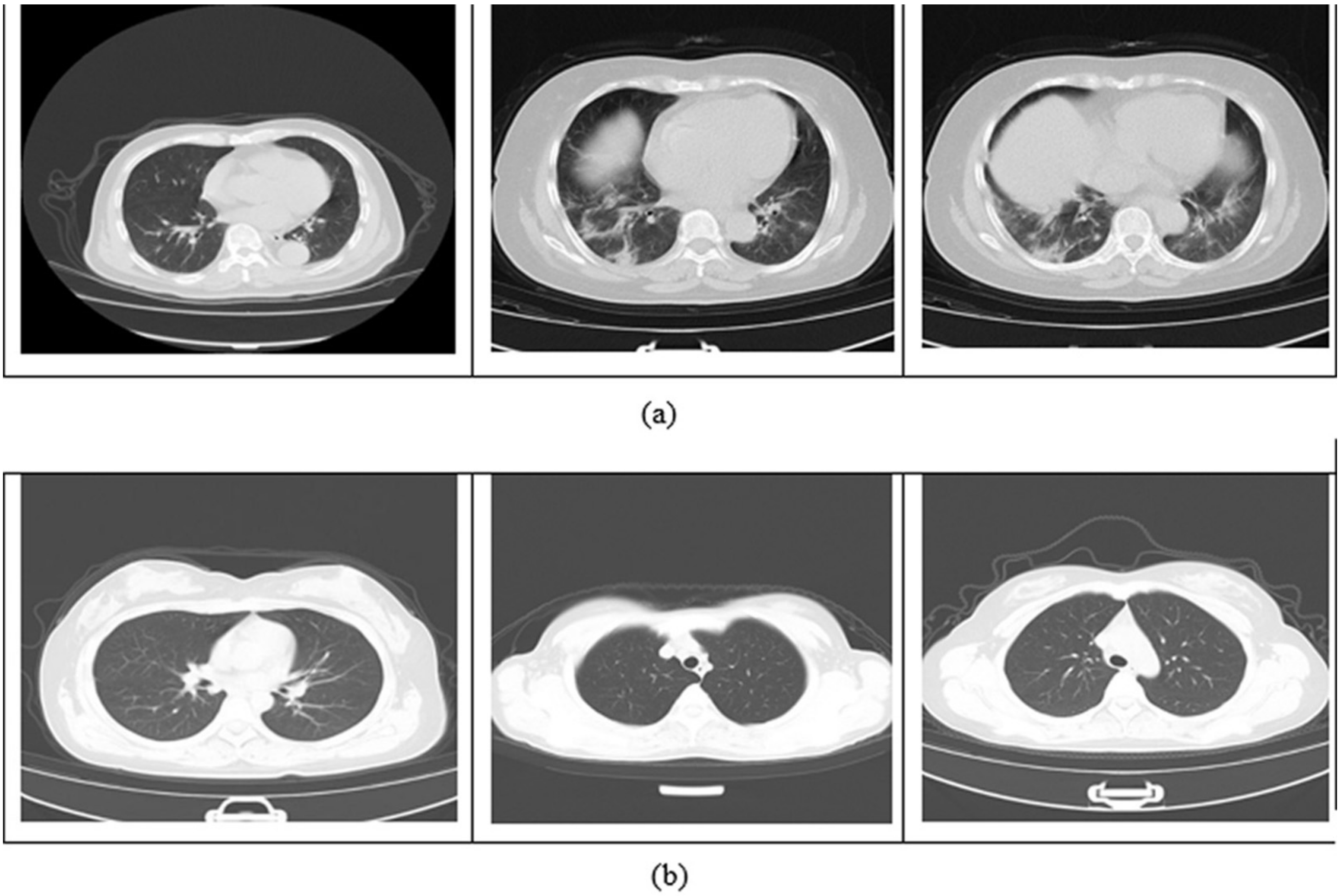

Fig. 1. CT-scan images of (a) COVID and (b) Non-COVID

3.2 COVID-19 classification strategy

The proposed method classifies COVID-19 infected persons by analyzing lung CT-scan images and chest X-ray images. Three pre-trained CNN models have been used that extract deep-level features from CT-scan images or X-ray images individually.

The models are VGG16 [28], VGG16-InceptionV3-ResNet50 [29], and Francois CNN [30]. Then the prediction results from the models have been taken to develop a voting ensemble of classifiers that distinguishes between COVID-19 and non-COVID cases. All the models are trained and validated individually with a large dataset containing 9412 CT-scan images with 4756 COVID-19 positive cases; and 3257 X-ray images with 1647 COVID-19 positive cases.

As the data are of image type, these are pre-processed before moving to the next steps. Then pre-processed data is used to train pre-trained models. The models are evaluated with different evaluation metrics. The results of the pre-trained models' evaluation metrics are used to compare the performance of the COV-CTX model. Finally, the results are combined to develop an ensemble with a voting classifier. Figure 3 shows the overall architecture of the COV-CTX model.

The proposed system uses a transfer learning process. The basic concept of transfer learning is to use the information of an existing CNN model to solve a new classification-based problem. Using this process, pre-trained CNN models can become very efficient to provide better accuracy with limited datasets for a new classification model. Hence, a transfer learning method has been adopted which avoids the need for a large number of datasets.

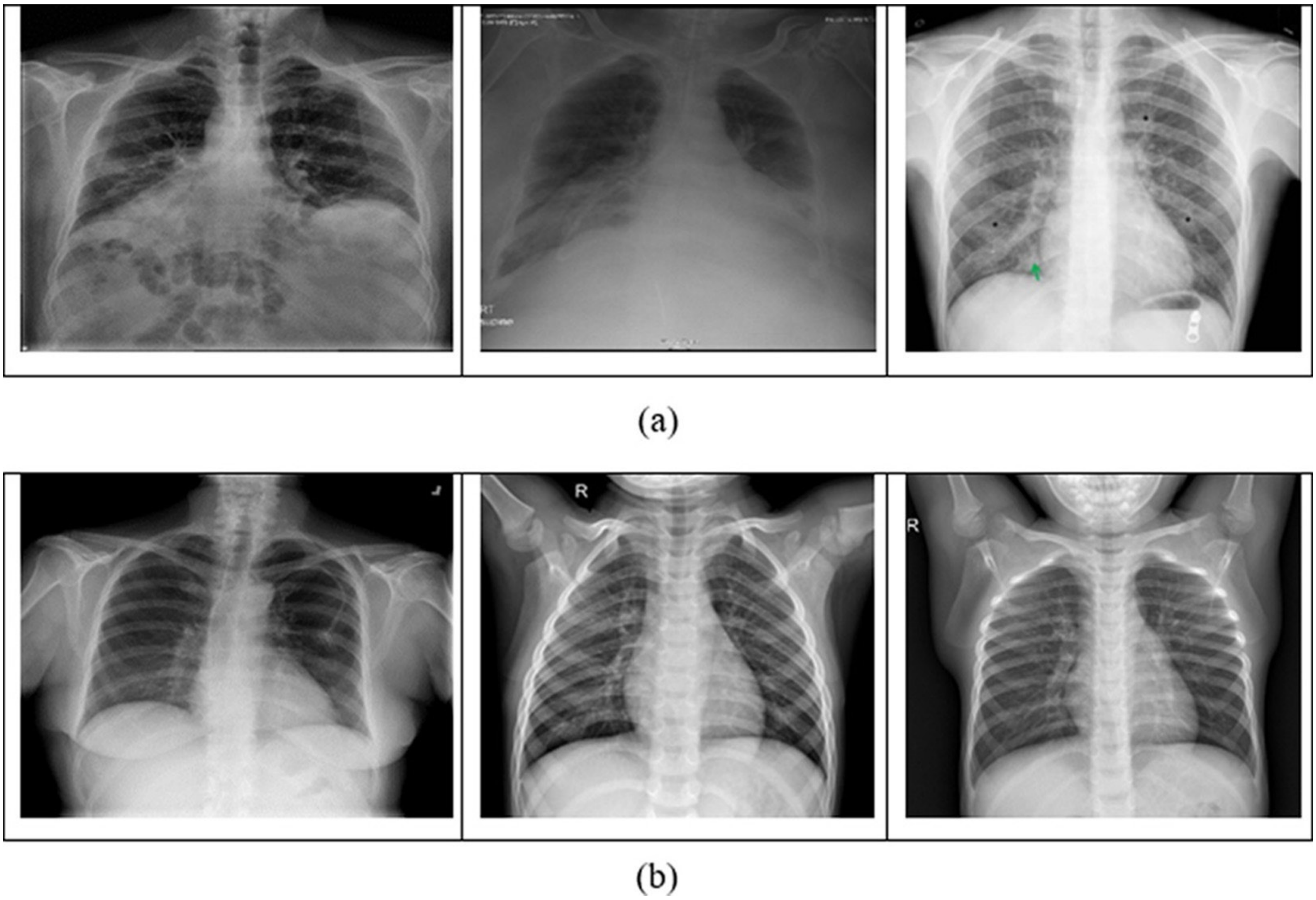

Fig. 2. X-ray images of (a) COVID and (b) Non-COVID

Three different pre-trained models have been used for transfer learning, which are VGG16, VGG16-InceptionV3-ResNet50 and Francoise CNN. All the models are already trained on the ImageNet dataset and can converge quickly over works like segmentation, object detection, etc. The models can identify different patterns and edges from images which are considered as high-level features. VGG16 helps to reduce parameters by using the same size of a 3x3 convolution kernel. It is better than the pre-trained model Alexnet. 16 layer based VGG16 is used with kernel size 3x3. It is used for its better bottleneck features and fine-tuning. The layer depth of VGG-16 is beneficial for classification accuracy. VGG16-InceptionV3-ResNet50 is a combination of VGG16, InceptionV3, and ResNet50 models where ResNet50 layers use less memory and quick deduction time; and InceptionV3 layers extract input data features at varying scales by using different size of convolutional filters and burns less computing power. This architecture provides the advantages of the lower number of weights and multilevel feature extraction. The ResNet50 could contain around 3 billion floating-point operations per second. Residual layers are used by ResNet50 to alleviate vanishing gradient and to make sure that higher and lower layers could work equally by learning identity function. Francoise CNN includes 12 layers. It uses 50% dropout to reduce overfit that optimizes for a large scale of networks. Though Francoise CNN model has less depth of layer than other models, it shows good performance. This trait of having few layers reduces the probability of increasing weight and complexity.

CNN models are trained with the customized dataset. Before using the dataset for training and testing, the images are resized to 150x150 pixels. The models are trained with CT-scan images and X-ray images individually. Finally, these three models are aggregated using the voting ensemble to ensure better performance results than individual model.

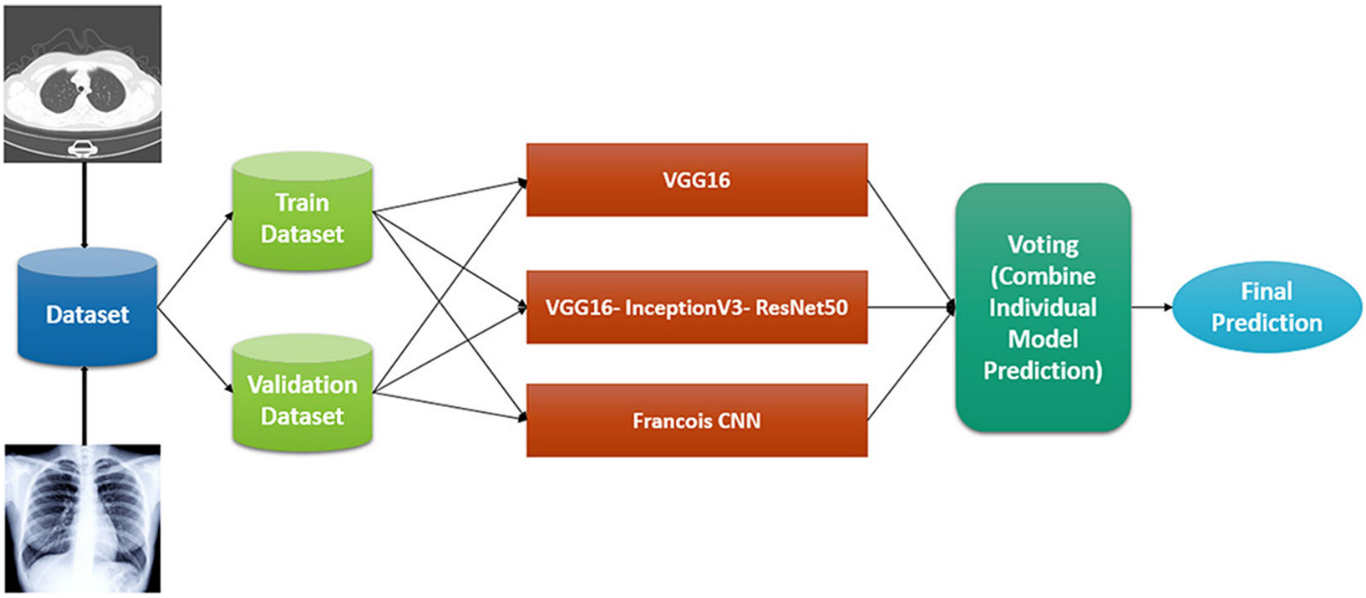

Fig. 3. System architecture of COV-CTX model

To develop the proposed ensemble model, the COV-CTX voting classifier method is used. It is a method that generates the outputs based on the prediction of different models and their majority vote. To achieve better performance, a hard voting classifier has been used rather than soft voting. The hard voting classifier predicts the class with the highest summation of votes from different models. COV-CTX predicts class labels based on majority voting from the models: Francois, VGG16, and VGG16-InceptionV3-ResNet50. For every image in the dataset, different models predict different classes. The voting ensemble predicts class labels for each image based on the majority class prediction of models.

The algorithm used for the classification purpose is described below.

Step 1: Chest X-ray image datasets are collected from different resources, for both COVID-19 positive and negative cases. A larger dataset is created by merging data from all these resources.
Step 2: Datasets are randomly divided for training and validation purposes.
Step 3: The training and validation datasets are used to train various pre-defined models for transfer learning.
Step 4: Among these models, the 3 best models are chosen based on their performances.
Step 5: These models were then ensembled by the hard-voting ensemble.
Step 6: The validation dataset is used to validate the new voting ensembled model. The hard voting ensemble model classifies the images as COVID-19 positive or negative based on the majority voting of these 3 models.
Step 7: The CT-Scan images are taken as input and Steps 1 to 6 are executed for these images.

4 RESULTS

This section is comprised of two sub-sections: experimental setup, and results analysis.

4.1 Experimental setup

Two types of browser notebook systems are used: The Kaggle notebook and Google Colab notebook. Python is used as it is concise and not complex. The necessary libraries are imported to run the project like TensorFlow and Keras version 2.4.0. Nine hours' sessions, 13 GB RAM, and 19.6 GB DISK are provided in Kaggle. On the other hand, 12.72 GB RAM and 107.77 GB DISK are provided in Google Colab. Google drive is used to import the dataset of CT-scan and X-ray images.

4.2 Analysis of the results

Figure 4 presents CT-scan-based training and validation accuracy according to epochs. For VGG16, the training accuracy is 98.97% and validation accuracy is 98.25%; for VGG16-InceptionV3-ResNet50, training accuracy is 99.96%, and validation accuracy is 98.25%; and for Francois CNN, the training accuracy is 99.72%, and validation accuracy is 97.82%. VGG16 shows training loss equals 0.0135, and validation loss equals 0.1449; VGG16-InceptionV3-ResNet50 shows training loss equals 0.0162, and validation loss equals 0.2252; and Francois CNN shows training loss equals 0.0066, and validation loss equals 0.1500.

Figure 5 presents X-ray-based training and validation accuracy according to epochs. For VGG16, the training accuracy is 98.82% and validation accuracy is 97.50%; for VGG16-InceptionV3-ResNet50 training, accuracy is 99.99%, and validation accuracy is 96.25%; and for Francois CNN, the training accuracy is 99.88%, and validation accuracy is 97.50%. VGG16 shows training loss equals 0.0507 and validation loss equals 0.0768; VGG16-InceptionV3-ResNet50 shows training loss equals 0.0022, and validation loss equals 0.1754, and Francois CNN shows training loss equals 0.0058, and validation loss equals 0.0989.

The performance of the proposed system is measured by accuracy, precision, recall/specificity, sensitivity, F1-score, Cohen kappa, ROC-AUC. All metrics are calculated from the confusion matrix.

Table 2 shows the performance evaluation of the system over CT-scan images. VGG16 achieves 95.17% accuracy, 94.99% precision, 94.48% sensitivity, 95.57% specificity and 94.74% F1-score. VGG16-InceptionV3-ResNet50 shows 95.06% accuracy, 93.36% precision, 95.91% sensitivity, 95.40% specificity and 95.13% F1-score. Francois CNN model demonstrates 95.75% accuracy, 94.33% precision, 94.35% sensitivity, 97.19% specificity and 95.74% F1 score. Finally, the voting classifier over these three models shows better performance than each model. The proposed COV-CTX shows 96.37% accuracy, 96.71% precision, 95.35% specificity, 97.24% sensitivity, 96.02% F1-score, 92.68% Cohens kappa.

Table 3 shows the performance evaluation of the system over X-ray images. VGG16 achieves 97.54% accuracy, 96.65% precision, 98.67% sensitivity, 98.44% specificity and 97.54% F1-score. VGG16-InceptionV3-ResNet50 has 97.47% accuracy, 98.16% precision and 98.25% sensitivity, 96.68% specificity and 97.41% F1 score. Francois CNN model demonstrates 97.54% accuracy, 96.08% precision, 96.04% sensitivity, 99.06% specificity and 97.55% F1-score. Finally, the voting classifier over these three models shows better performance than the models. The proposed system shows validation accuracy of 99.23%, 99.37% precision, 99.07% specificity, 99.39% sensitivity, 99.22% F1-score, 98.46% Cohens kappa score.

In the validation dataset, there are 1881 CT-scan images including 924 COVID positive and 957 non-COVID images. The proposed model predicts 894 COVID and 919 non-COVID correctly.

In Figure 6 the confusion matrix of all models and voting classifiers for CT images. VGG16 predicts 34 COVID images incorrectly and 57 non-COVID images incorrectly. VGG16-InceptionV3-ResNet50 predicts 51 COVID images incorrectly and 46 non-COVID images incorrectly. Francois CNN predicts 54 COVID images incorrectly and 26 non-COVID images incorrectly. Finally, the proposed system predicts 30 COVID images incorrectly and 38 non-COVID images incorrectly.

In the validation dataset, there are 651 X-ray images including 329 COVID and non-COVID images. Figure 7 presents the confusion matrix of all models and the voting classifier for X-ray classifier for X-ray images incorrectly and 11 non-COVID images incorrectly. VGG16-InceptionV3-ResNet50 predicts 6 COVID images incorrectly and 11 non-COVID images system predicts 3 COVID images incorrectly and 2 non-COVID images incorrectly. The system predicts 327 COVID and 319 non-COVID correctly.

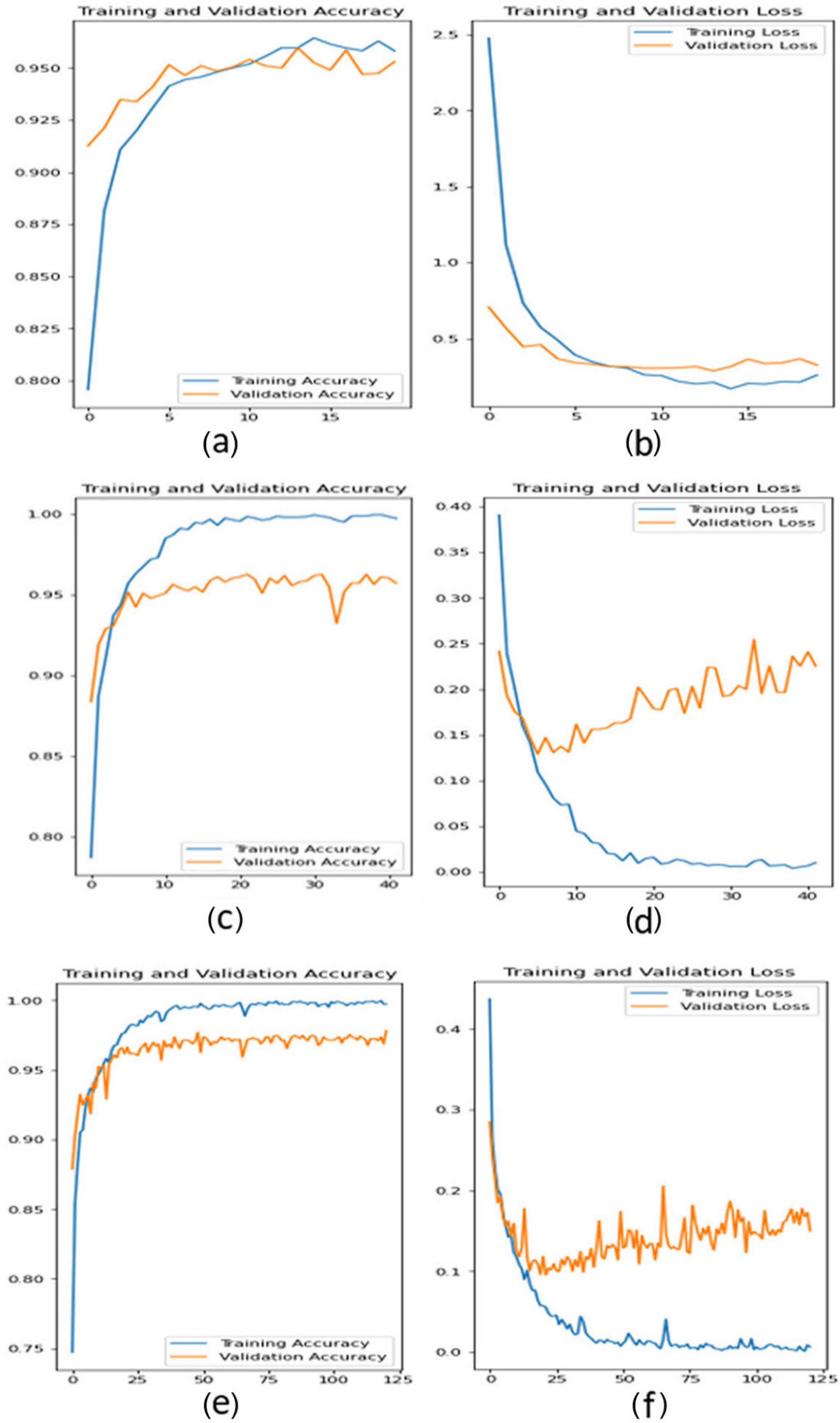

Fig. 4. Performance analysis based on CT-scan image for (a) Training and Validation Accuracy of VGG16 (b) Training and Validation Loss of VGG16 (c) Training and Validation Accuracy of VGG16-InceptionV3-ResNet50 (d) Training and Validation Loss of VGG16-InceptionV3-ResNet50 (e) Training and Validation Accuracy of Francois CNN (f) Training and Validation Loss of Francois CNN

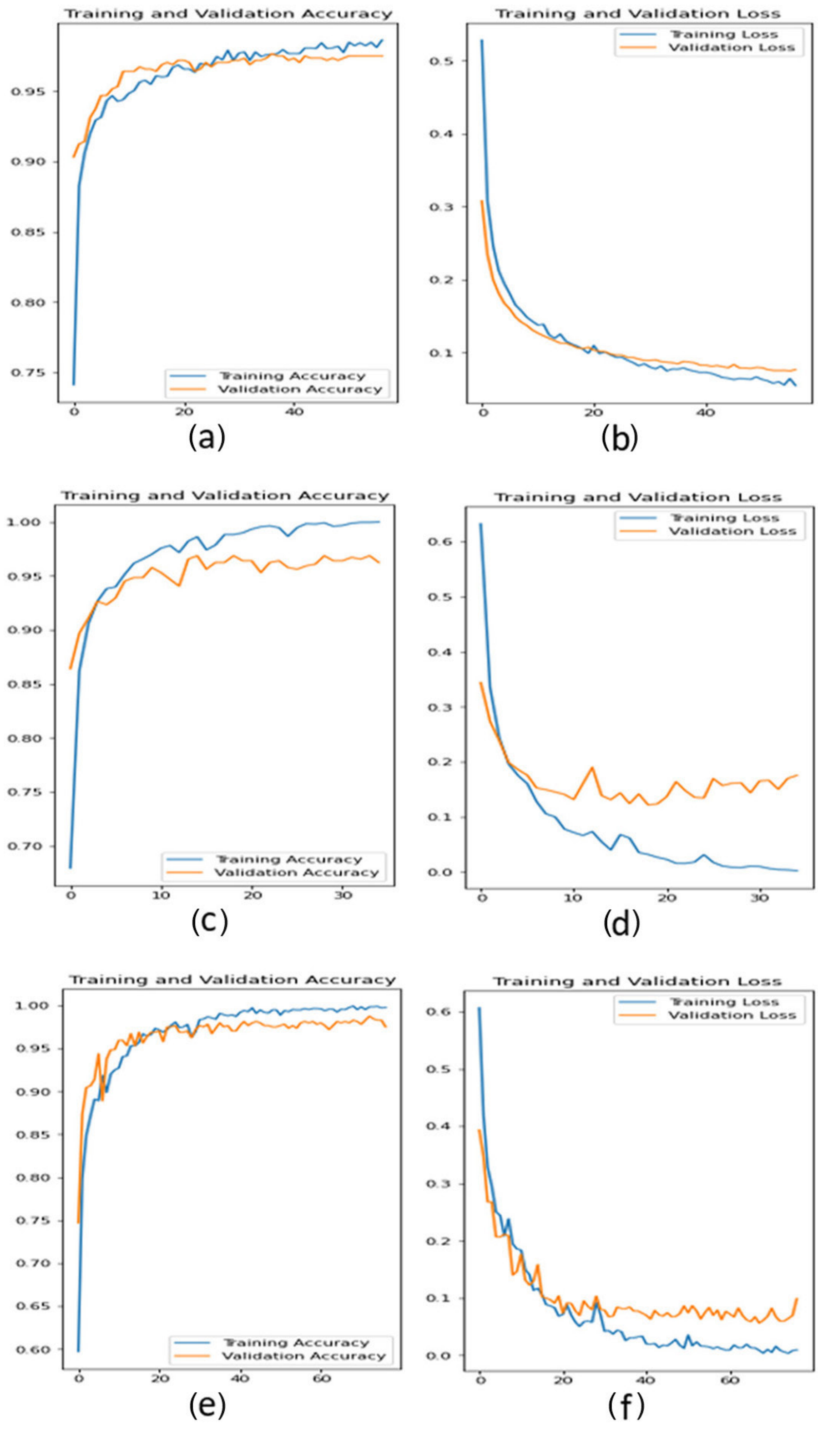

Fig. 5. Performance analysis based on X-ray image for (a) Training and Validation Accuracy of VGG16 (b) Training and Validation Loss of VGG16 (c) Training and Validation Accuracy of VGG16-InceptionV3-ResNet50 (d) Training and Validation Loss of VGG16- InceptionV3-ResNet50 (e) Training and Validation Accuracy of Francois CNN (f) Training and Validation Loss of Francois CNN

Table 2. Performance evaluation of CNN architectures on CT-scan images

Model Name	Accuracy	Precision	Recall / Sensitivity	Specificity	F1 Score	Cohens Kappa
VGG16	95.17	94.99	94.48	95.57	94.74	90.28
VGG16-InceptionV3-ResNet50	95.06	93.36	95.91	95.4	95.13	90.89
Francois CNN	95.75	94.33	94.35	97.19	95.74	91.95
COV-CTX (Proposed System)	96.37	96.71	97.24	95.35	96.02	92.68

Table 3. Performance evaluation of CNN architectures on the X-ray images

Model Name	Accuracy	Precision	Recall / Sensitivity	Specificity	F1 Score	Cohens Kappa
VGG16	97.54	96.65	98.67	98.44	97.54	95.08
VGG16-InceptionV3-ResNet50	97.47	98.16	98.25	96.68	97.41	94.95
Francois CNN	97.54	96.08	96.04	99.06	97.55	95.09
COV-CTX (Proposed System)	99.23	99.37	99.39	99.07	99.22	98.46

For the CT-scan-based system, ROC curves [31] are plotted in Figure 8. AUC for VGG16 is 0.9512, for InceptionV3-ResNet50 is 0.9553, for Francois CNN is 0.9577, for COV-CTX is 0.9629. More area under the ROC curve indicates that the model is efficient for medical diagnosis.

For the X-ray-based system, ROC curves are plotted in Figure 9. For VGG16 AUC is 0.9755, for InceptionV3-ResNet50 AUC is 0.9878, for Francois CNN AUC is 0.9756, for COV-CTX AUC is 0.9923. Thus, the model works efficiently for the detection of COVID positive events using chest X-ray images.

Table 4 shows the comparison between the proposed method and existing works. For Mucahid et al. [7], Kevser et al. [12], Xin He et al. [13], and Zahangir et al. [15], accuracy lies between 80% and 90%. Among them, minimum accuracy was 80% for Kevser et al. [12] and maximum accuracy was 88.63% for Kevser et al. [12]. Mucahid et al. [7] and Kevser et al. [12] used a comparatively very small dataset than Xin He et al. [13] and Zahangir et al. [15]. Mucahid et al. [7] used only 150 CT images and Kevser et al [12] used only 140 images in their methodologies. The rest of the existing methods achieve accuracy between 90% and 99%. Minimum accuracy was 90% for Saban et al. [14] and maximum accuracy was 98.27% for Umut et al. [8]. Umut et al. [8], Ali et al. [10] and Saban et al. [14] used a comparatively very small dataset. Umut et al. [8] used only 150 CT images. Ali et al. [10] used only 71 X-ray images and Saban et al. [14] used only 260 CT scan and X-ray images. Finally, the proposed COV-CTX which consists of 9412 CT-scan images and 3257 X-ray images, demonstrates 96.37% accuracy for CT-scan images and 99.23% accuracy for X-ray images.

Table 4. The comparison between the proposed method and existing works

Author	Dataset Details	Method and Model	Input	Performance
Mucahid et al. [8]	150 CT abdominal images in which 53 images are COVID-19 positive	Extraction models: Grey Level Co-occurrence Matrix, Local Directional Pattern, Grey Level Run Length Matrix, Grey-Level Size Zone Matrix, Discrete Wavelet Transform and classified by the SVM (Support Vector Machines)	CT-scan image	87.6% accuracy
Umut et al. [9]	150 CT images with 53 infected CT images	A pre-trained CNN, SVM	CT-scan image	98.27% accuracy
Arpan et al. [10]	1583 normal, 2780 bacterial pneumonia, 1493 viral pneumonia, and 155 COVID-19 infected chest X-ray images	Deep neural network-based AI detector named COVIDAID	X-ray image	90.5% accuracy
Ali et al. [11]	71 chest X-ray images with 48 cases for COVID-19 positive and 23 for COVID-19 negative	A hybrid model consisting of support vector machine (SVM), random forest (RF), and many more	X-ray image	95.2% accuracy
Taban et al. [12]	1575 normal cases, 2771 confirmed bacterial infection cases, and 1494 viral (Non-COVID-19) confirmed cases	CNN-X architecture consisting of 12 off-the-shelf CNN models	X-ray image	97.82% accuracy
Kevser et al. [13]	70 positive 70 negative COVID-19 posteroanterior X-ray scan images	Pre-trained CNN architectures: VGG16, VGG19, ResNet, DenseNet, and InceptionV3	X-ray image	80% accuracy
Xin He et al. [14]	CT scan images from 4,154 patients, distributed in three classes (novel coronavirus pneumonia (NCP), common pneumonia (CP), and normal controls (Normal))	Two types of state-of-the-art (SOTA) Deep Learning models: 3D CNN including DenseNet3D121, R2Plus1D, MC3 18, ResNeXt3D101, PreAct ResNet, and ResNet3D series and 2D CNNs, including DenseNet121, DenseNet201, ResNet50, ResNet101 and ResNeXt101	CT-scan image	88.63% accuracy
Saban et al. [15]	260 images, including 40 ARds, 101 Covid, 24 No findings, 24 pneumocystispneumonia images, 43 Sars, 28 streptococcus images	Feature extraction: Grey Level Co-occurrence Matrix (GLCM), Local Binary Grey Level Co-occurrence Matrix (LBGLCM), Grey Level Run Length Matrix (GLRLM), and Segmentation-based Fractal Texture Analysis (SFTA) and classification: SVM	CT-scan image and X-ray image	90% accuracy
Zahangir et al. [16]	5,216 X-ray images, where 1,341 normal and 3,875 pneumonia infected	Multi-Task Deep Learning, NABLA-N based segmentation model, IRRCNN based detection model	CT-scan image and X-ray image	84.67% accuracy
COV-CTX (Proposed Method)	9412 CT-scan images and 3257 X-ray images	Voting Ensemble of VGG16, VGG16-InceptionV3-ResNet50, and Francois CNN	CT-scan image and X-ray image	96.37% (CT-scan), 99.23% (X-ray)

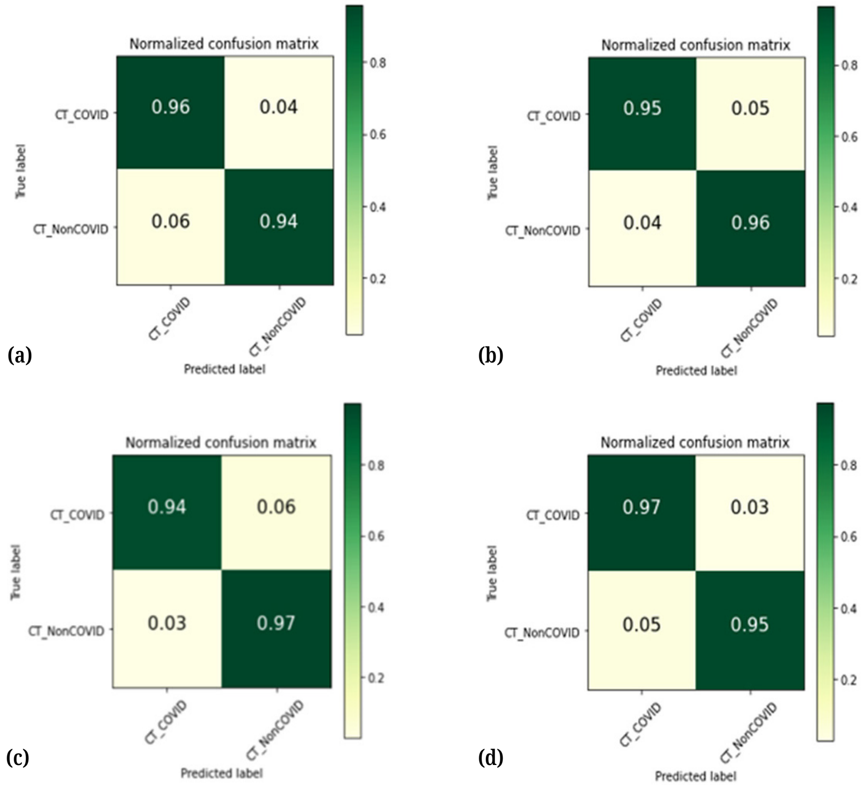

Fig. 6. Confusion Matrix of the CNN models and proposed system over CT-scan images for (a) VGG16 (b) VGG16-InceptionV3-ResNet50 (c) Francois CNN (d) COV-CTX (Proposed System)

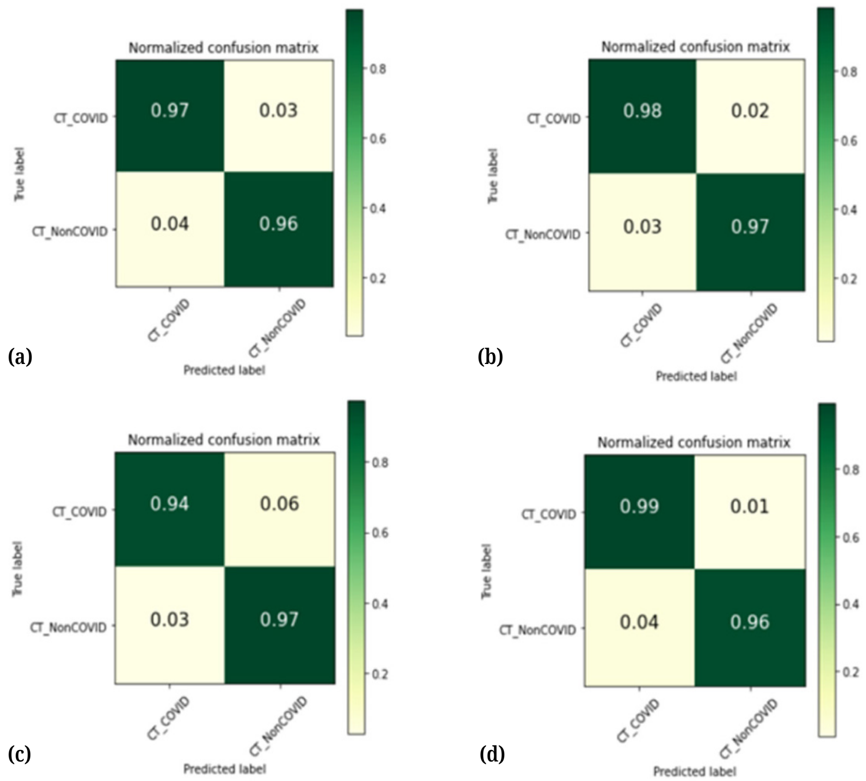

Fig. 7. Confusion Matrix of the CNN models and proposed system over X-ray images for (a) VGG16 (b) VGG16-InceptionV3-ResNet50 (c) Francois CNN (d) COV-CTX (Proposed System)

5 CONCLUSIONS

The proposed system, COV-CTX can perform automated detection of COVID-19 from CT-scan and X-ray images. The images are analyzed by CNN architectures to extract unique features for the detection of COVID-19. A large dataset has been applied to get the system more reliable. To avoid specific country effects and get generalizations, the datasets of different formats and resolutions have been used from multiple sources. For the CT-scan-based model, 4756 COVID-19 infected and 4656 Non-COVID images are applied. Again, for X-ray based model 1647 COVID-19 infected and 1610 Non-COVID images are applied. The dataset is partitioned into 80%:20%, for training and validation. The performance of COV-CTX has been improved by using a hard voting classifier that pulls up the result to 96.37% accuracy for the CT-scan-based model and 99.23% accuracy for X-ray based model. The research proposes two models that separately detect COVID-19 positive and negative cases by studying both Chest X-ray and lung CT-Scan images. The models are not dependent on each other. Thus, both types of images are not mandatory for COVID-19 positivity or negativity detection. The CT-scan and X-ray images used in the training and validation are not from the same subject. In the future, the proposed system can be enhanced in such a way that it can classify not only COVID-19, and normal classes but also other lung infections like viral or bacterial pneumonia.

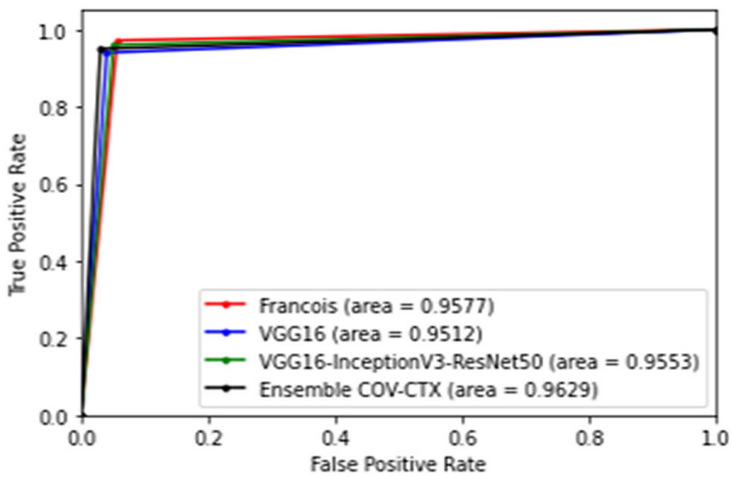

Fig. 8. ROC curve for the CT-scan based system

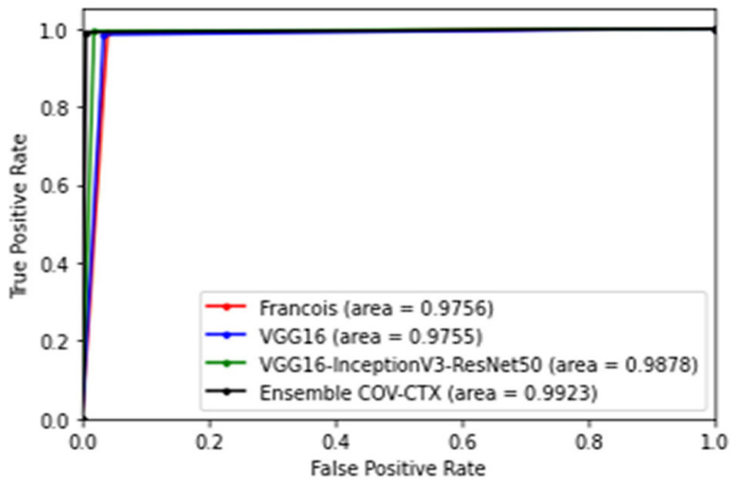

Fig. 9. ROC curve for the X-ray based system

6 REFERENCES

[1] Abo WHO Coronavirus (COVID-19) Dashboard. (n.d.). [Online]. Available: https://covid19.who.int/ [Accessed: 20-Apr-2021]

[2] Osmanlliu, E., Rafie, E., Bédard, S., Paquette, J., Gore, G., & Pomey, M. "Considerations for the design and implementation of COVID-19 contact tracing apps: Scoping review," JMIR Mhealth Uhealth, vol. 9, no. 6, p. e27102, 2021. https://doi.org/10.2196/27102

[3] Touzani, R., Schultz, E., Holmes, S. M., Vandentorren, S., Arwidson, P., Guillemin, F., Rey, D., Rouquette, A., Bouhnik, A., & Mancini, J. "Early acceptability of a mobile app for contact tracing during the COVID-19 pandemic in France: National web-based survey," JMIR Mhealth Uhealth, vol. 9, no. 7, p. e27768, 2021. https://doi.org/10.2196/27768

[4] Dong, D. et al. "The role of imaging in the detection and management of COVID-19: A review," in IEEE Reviews in Biomedical Engineering, vol. 14, pp. 16–29, 2021. https://doi.org/10.1109/RBME.2020.2990959

[5] Ulhaq, J., Born, A., Khan, D. P. S., Gomes, S., Chakraborty, & Paul, M. "COVID-19 control by computer vision approaches: A survey," in IEEE Access, vol. 8, pp. 179437–179456, 2020. https://doi.org/10.1109/ACCESS.2020.3027685

[6] Ulhaq, A., Khan, A., Gomes, D., & Paul, M. "Computer vision for covid-19 control: A survey, 2020. arXiv preprint arXiv:2004.09420. https://doi.org/10.31224/osf.io/yt9sx

[7] Barstugan, Mucahid, Umut Ozkaya, & Saban Ozturk. "Coronavirus (COVID-19) classification using ct images by machine learning methods," 2020. arXiv preprint arXiv:2003.09424.

[8] Özkaya, Umut, Şaban Öztürk, & Mucahid 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. Springer, Cham; 2020.p. 281–295. https://doi.org/10.1007/978-3-030-55258-9_17

[9] Mangal, A., Kalia, S., Rajgopal, H., Rangarajan, K., Namboodiri, V., Banerjee, S., & Arora, C. "COVIDAID: COVID-19 detection using chest X-ray," 2020. arXiv preprint arXiv:2004.09803.

[10] Alqudah, Ali Mohammad, Shoroq Qazan, Hiam Alquran, Isam Abu Qasmieh, & Amin Alqudah. "Covid-19 detection from x-ray images using different artificial intelligence hybrid models," Jordan Journal of Electrical Engineering, vol. 6, no. 2, pp. 168–178, 2020. https://doi.org/10.5455/jjee.204-1585312246

[11] Majeed, T., Rashid, R., Ali, D., & Asaad, A. "COVID-19 detection using cnn transfer learning from x-ray images," medRxiv, 2020. https://doi.org/10.1101/2020.05.12.20098954

[12] Sahinbas, K., & Catak, F. O. "24 – Transfer learning based convolutional neural network for COVID-19 detection with x-ray images. Data Science for COVID-19," Data Science for COVID-19, Academic Press, 2021, pp. 451–466, https://doi.org/10.1016/B978-0-12-824536-1.00003-4

[13] He, Xin, et al. "Benchmarking deep learning models and automated model design for COVID-19 detection with chest ct scans," medRxiv, 2020. https://doi.org/10.1101/2020.06.08.20125963

[14] Ozturk, Saban, Umut Ozkaya, & Mucahid Barstugan. "Classification of coronavirus images using shrunken features," medRxiv, 2020. PMID: 32904960. https://doi.org/10.1002/ima.22469

[15] Alom, M. Z., Rahman, M. M., Nasrin, M. S., Taha, T. M., & Asari, V. K. "COVID_mtnet: COVID-19 detection with multi-task deep learning approaches," 2020. arXiv preprint:2004.03747.

[16] Kaichao Wu, April 20, 2021, "COVID-19 Lung images", IEEE Dataport, https://dx.doi.org/10.21227/fxcx-zh58

[17] Mr7495. (n.d.). Mr7495/COVID-CTset. Retrieved April 20, 2020, from https://github.com/mr7495/COVID-CTset

[18] T. Yan, "Ccap," Jul 2020. [Online]. Available: https://ieee-dataport.org/documents/ccap [Accessed: 08-Mar-2021].
[19] M. Merset, "COVID19 ct-scan images dataset," Aug 2020. [Online]. Available: https://www.kaggle.com/mohanedmerset/COVID19-ctscan-images-dataset [Accessed: 01-Feb-2021].
[20] J. P. Cohen, P. Morrison, L. Dao, K. Roth, T. Q. Duong, and M. Ghassemi, "COVID-19 Image Data Collection: Prospective Predictions Are the Future," 2020, [Online]. Available: https://doi.org/10.59275/j.melba.2020-48g7
[21] COVID 19 chest X-ray [Online]. Available: https://github.com/agchung [Accessed: 08-Mar-2021].
[22] COVID-19 DATABASE | SIRM [Online]. Available: https://www.sirm.org/en/category/articles/COVID-19-database/ [Accessed: 08-Mar-2021].
[23] The cancer imaging archive (TCIA) [Online], Available: https://wiki.cancerimagingarchive.net/display/Public/Imaging+Clinical+Trials [Accessed: 08-Mar-2021].
[24] Gaillard F. Radiopaedia.org, the wiki-based collaborative Radiology resource. Radiopaedia.org; 2014 [Online]. Available: http://radiopaedia.org/ [Accessed: 08-Mar-2021].
[25] Alqudah, Ali Mohammad, & Shoroq Qazan. "Augmented COVID-19 X-ray images dataset," Mendeley Data 4 (2020).
[26] P. Mooney, "Chest X-Ray Images (Pneumonia)," Kaggle, 24-Mar-2018. [Online]. Available: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia. [Accessed: 13-Apr-2021].
[27] "NIH Chest X-rays | Kaggle." 2018, [Online]. Available: https://www.kaggle.com/nih-chest-xrays/data
[28] Simonyan, Karen, & Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition," 2014. arXiv:1409.1556.
[29] He, K., Zhang, X., Ren, S., & Sun, J. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 770–778. https://doi.org/10.1109/CVPR.2016.90
[30] Emrecetin, "Francois CNN Model on COVID-19 images," Kaggle, 04May-2020. [Online]. Available: https://www.kaggle.com/emrecetin/francoiscnn-model-on-COVID-19-images. [Accessed: 01-Feb-2021].
[31] Narkhede, Sarang. "Understanding auc-roc curve," Towards Data Science vol. 26, pp. 220–227, 2018.

7 AUTHORS

Muhammad Sheikh Sadi is a professor in the Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Bangladesh. He was DAAD Research Scholar in the University of Koblenz-Landau, Germany in 2018. He was also a Visiting Research Scholar in Dependable Embedded Systems and Software (DEEDS) Research Group, TU Darmstadt, Germany in 2008. He has completed his PhD thesis from the department of Electrical and Computer Engineering, Curtin University, Australia in 2010. His areas of research interests are: Health Technology, Soft Errors Tolerance, Humanitarian Technology, and Internet of Things (IOT). He is a senior member of IEEE, is reviewers of several reputed journals and has published more than 90 research papers in peer reviewed journals and conferences. (email: sadi@cse.kuet.ac.bd).

Mohammed Alotaibi received the B.S. in computer Science from King Saud University in July 2008 and M.S. degrees in Computer and Information Networks, Essex University, UK (Jan, 2011)., respectively He got Ph.D. in health informatics from Kingston University London in March 2015. He has served as assistant Prof and then associate prof at the faculty of computers and information technology at the University of Tabuk since August 2015 until now. He owned three research project funds from different organizations. He is now a research leader of a research group that focus on using robotic and AI in chronic diseases which owned a research fund worth 100.000 Saudi riyals. (email: mmalotaibi@ut.edu.sa).

Prottoy Saha is currently working as an Assistant Professor in CSE department of Khulna University of Engineering & Technology (KUET), Khulna, Bangladesh. He received his B.Sc. degree in Computer Science and Engineering (CSE) from the Bangladesh University of Engineering & Technology (BUET), Dhaka, Bangladesh in 2017 and M.Sc. degree in CSE from KUET in 2021. In 2018, he joined the Department of Computer Science and Engineering, Khulna University of Engineering & Technology (KUET), as a Lecturer. He has published several research papers in peer reviewed journals and conferences. In addition, he is reviewer of several reputed journals and conferences. His research interests include machine learning and its application, deep learning, Internet of Things (IoT) etc. (email: prottoy@cse.kuet.ac.bd).

Fahamida Yeasmin Nishat is currently working as a Lecturer (Contractual) in CIS department of Daffodil International University (DIU), Dhaka, Bangladesh. She received her B.Sc. degree in Computer Science and Engineering (CSE) from the Khulna University of Engineering & Technology (KUET), Khulna, Bangladesh in 2022. On July 2022, she joined the Department of Computing and Information System (CIS), Daffodil International University (DIU), as a Lecturer. She has recently published a review paper about COVID-19 and AI based technology in a peer reviewed journal. Her research interests include machine learning and its application, deep learning, Image Processing, Natural Language Processing etc. (email: nishat1607085@stud.kuet.ac.bd).

Jerin Tasnim is currently working as a Lecturer in CSE department of Bangladesh Army University of Science and Technology (BAUST), Saidpur Cantonment, Bangladesh. She received her B.Sc. degree in Computer Science and Engineering (CSE) from the Khulna University of Engineering & Technology (KUET), Khulna, Bangladesh in 2022. In January 2023, she joined the Department of Computer Science and Engineering (CSE), Bangladesh Army University of Science and Technology (BAUST), Saidpur Cantonment, as a Lecturer. She has recently published a review paper about COVID-19 and AI based technology in a peer reviewed journal. Her research interests include machine learning and its application, deep learning, Image Processing, Natural Language Processing etc.

Tareq Alhmiedat is an Associate Professor in the Department of Computer Science, and the head of Robotics & Artificial Intelligence Unit, in the Industrial Innovation & Robotics Center at University of Tabuk, Tabuk, Saudi Arabia. His research interests include tracking mobile targets through Wireless Sensor Networks, robot navigation and orientation, and robot vision systems. Dr. Alhmiedat has been involved in various research projects including: SafetyNET, IndoorTrack, Diabetic Robotics, and WSN environment monitoring. (email: t.alhmiedat@u.edu.sa).

Hani Almoamari is Assistant Professor in the Department of Information Technology at Islamic University of Madinah, where he has been since June 2020. From 2017 to 2018 he served as Department Chair of Computer Science at University of Tabuk. During 2018–2019, he supervised the Quality Assurance Unit at the Deanship of Quality and Development. From 2018 to May 2020 he is served as the Vice-dean of Information Technology for Quality and Development. He is currently serving as the Vice-dean of Quality and Development of Computer Science College at Islamic University of Madinah. He received his Bachelor degree from Taibah

University in 2006, and received the Master degree from University of Science Malaysia in 2010. He received his Ph.D. in Computer Science from the University of Stirling in 2017. His research interests span both computer networking and network science. His work in PhD focused on simulating and Modelling the Computer Worms in Peer to Peer Networks. In addition, he has focused on investigating the utilization of Agent-based Modelling (ABM) in Simulating the worms in P2P networks. (email: hani.almoamari@iu.edu.sa).

Zaid Bassfar received the B.S. in Computer Science in 2007, and M.S. degrees in Information Technology and Communication in 2010. He received the PhD degree in Web Applications in 2014. He has been an associate professor since 2020 at College of computer and Information Technology at University of Tabuk. His research interest includes Web Applications – Virtual Reality – Emerging Technology – Virtual Learning – E-learning – M-learning – Multimedia – Human Computer Interaction. (email: zbassfar@ut.edu.sa).