Prediction of COVID-19 Patients from X-Rays using Ensemble Deep Transfer Learning Techniques

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Prediction of COVID-19 Patients from X-Rays using Ensemble Deep Transfer Learning Techniques

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Abstract

Deep learning is very effectively used in the medical field to predict diseases such as pneumonia classification, cancer, and so on. Convolutional Neural Network (CNN) is used to classify the chest X-rays of humans in normal and COVID-19 infected cases. To build a model, pre-trained models and transfer learning is used. In this paper, four pre-trained models VGG16, VGG19, ResNet50, and InceptionV3 are ensemble and build a new ensemble model. To train and test a model, a dataset of as many as 720 X-ray images has been used. Less number of images makes us apply image augmentation. The ensemble models such as VGG19 and ResNet50, VGG16 and ResNet50, VGG16 and InceptionV3, and VGG19 and InceptionV3 yield 96.53%, 98.61%, 99.31%, and 100% accuracy respectively.

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1 Introduction

The first case of coronavirus disease (COVID-19) was reported in Wuhan of China at the end of December, 2019. Since then, it has spread all over the world due to the infectious nature of coronavirus [1]. The World Health Organization (WHO) declared the outbreak of COVID-19 as a "Public Health Emergency of International Concern " on January 30, 2020. On March 11, 2020, this was declared as a pandemic. In many countries, the third wave of this pandemic very badly affected many sectors such as education, public sector, private sector, and business. The total number of confirmed infected cases is 279,829,699 and as many as 5,413,118 deaths as on December 26, 2021 [2]. As COVID-19 affected all regions like Americas (63,018,740), Europe (83,266,866), South-East Asia (84,085,805), Eastern Mediterranean (9,188,751), Africa (9,544,668), Western Pacific (2,489,293) confirmed cases [2].

The novel Coronavirus, also known as COVID-19 has affected the social and economic life of humans. Early detection and visualization of infected people is necessary to save the infected people. Researchers proposed various solutions based on natural language processing, knowledge engineering, and deep learning. The most common symptoms are fever, dry cough, and tiredness [3]. Less common symptoms that were noticed are: aches, pains, sore throat, diarrhea, conjunctive, headache, loss of taste or smell, a rash on the skin, and discoloration of fingers or toes [4]. To stop the outbreak of COVID-19, the infected persons have

to be quarantined. If the person is not isolated then that person may also infect many other persons. So isolation or quarantine is a better way to prevent the spread of this virus [5].

Various tests such as RT-PCR and RAT are available to identify if a person is infected or not. However, these are very costly and time-consuming. To overcome these problems, radiological imaging techniques are required. The well-known imaging techniques are chest CT scan and chest X-ray. X-ray images are less expensive than CT scan and X-ray can be got done easily [6]. These X-ray images are used to predict the effective part of the body, lungs, infection, pneumonia, tumors and so on. With these benefits X-ray images can also be used to predict the COVID-19. By using deep transfer learning techniques and pre-trained model X-ray images can be classified as COVID-19 and Normal [7].

A deep learning model can be introduced based on x-ray images of the human chest. In earlier times, deep learning techniques were used in medical imaging field. Whenever a person gets infected then the virus also attacks the human lungs and by using a chest X-ray we can classify that person as either infected or not. In this paper, an ensemble model prepared by the combination of VGG16 and InceptionV3 are applied on X-ray images to classify persons. The main contributions of this paper are as follows:

1. Four ensemble models namely VGG16+ResNet50, VGG19+ResNet50, VGG16+InceptionV3, and VGG19+InceptionV3 are designed for classification of coronavirus infection from the chest X-ray images. modified for COVID-19 classification..
2. Ensemble models are tested on chest X-ray dataset and attained better performance than their original models.

The remaining structure of the paper is as follows. Section 2 presents the related work done in the direction of COVID-19. Section 3 represents the proposed ensemble approach for identification of COVID-19. The results and discussion are mentioned in Section 4. The concluding remarks are drawn in Section 5.

2 Related Work

Researchers have been working extensively in this field to predict the COVID-19 patients via many DL models.

Ahmed et al. [1] classified the X-ray images based on COVID-19 by using deep learning models such as MobileNet, ResNet50 and Inception V3 with some manipulations. Better accuracy was achieved by MobileNet (95.18%) and Inception (95.75%). According to these results, they prepared a hybrid model with both of these and achieved classification accuracy of 96.49% and f-score of 92.49% in training. In the testing, accuracy and F1-score achieved were 94.19% and 88.64% respectively. Oksuz et al. [8] A Deep Learning model CVDNet was developed to classify the x-rays based on COVID-19, Pneumonia, and normal X-ray images. CVDNet was an ensemble with three light weight pre-trained models namely SqueezeNet, ShuffleNet, and EfficientNet-B0. This model yielded 98.30% accuracy, 97.78% sensitivity, and 97.61% F1-score (Oksuz et al., 2020). Hemdan et al. [9] proposed a framework named COVIDX-Net. This framework includes seven different types of architecture. Decent and comparable f1-scores 0.89 and 0.91 were achieved by this model for normal and COVID-19 respectively.

Gianchandani et al. [10] proposed two ensemble models by using pre-trained CNN models used to classify chest X-rays. These models were used to solve the binary and multi-class problems. They were able to classify COVID-19, viral pneumonia and bacterial pneumonia X-rays. Rahimzadeh and Attar [11] presented a model, which was an ensemble of Xception and ResNet50V2. This was used to classify normal, COVID-19, and pneumonia chest X-rays. This model was tested on 11302 chest X-rays and achieved overall accuracy about 91.40%. Sarkar et al. [12] developed a DL model based on DenseNet-121 to classify COVID and normal patients with 96.49% and 93.71% accuracy for two-class and three-class, respectively. Narin et al. [13] constructed multiple pre- trained CNN models to work on pneumonia infected patients to operate on X-ray images. The processed images were classified into four classes as COVID-19, Normal, Viral Pneumonia, and Bacterial Pneumonia. The highest accuracy was obtained by ResNet50 at 98%. Sethy et al. [14] extracted features from chest X-ray images used with SVM classifier as

to if the patient is infected or normal. As many as 13 different CNN models were used to achieve 95.38% accuracy by using ResNet50 and SVM. Das et al. [15] prepared a model by the combination of CNN models DenseNet201, ResNet50V2, and InceptionV3 to classify positive and negative chest X-rays. This model was tested on 1006 X-rays and achieved the classification accuracy 91.62%.

It is observed from the above-mentioned literature that the performance of existing models is still far from the optimal solution. Hence, there is a need to develop the ensemble model for COVID-19 classification.

3 Proposed Ensemble Model

In this paper, a dataset of normal and COVID X-rays images is used, which is publicly accessible [16]. All available X-ray images are of different sizes which could be complex to handle so this is resolved by using resize of all X-rays images of size 224×224. For this dataset, data augmentation technique is used to increase the number of images. In this paper, an ensemble model is built with the help of VGG16 and InceptionV3 (see Fig. 1). This ensemble model produces good results. To build this model steps as follows:

Step 1: **Image Acquisition**
Initially all the normal and COVID X-rays images are collected, which are publicly available from Kaggle [16] and GitHub [17], respectively.

Step 2: **Update Data**
In this step, all the labels are pulled-out from the dataset. In the end of this step, all images are converted from BGR to RGB channels and all image resolutions are converted into fixed size of 224×224.

Step 3: **Implementation of One-Hot Encoding**
On labels, as collected in the previous step, one-hot encoding is applied with the help of LabelBinarizer(). Label Binarizer is a class of Scikit-Learn which takes categorical data as input and returns a NumPy array.

Step 4: **Splitting Dataset and Augmentation Implementation**
The dataset is splitted into training and testing sets in the ratio of 80% and 20% respectively. Then, augmentation is implemented with parameters such as rotation range is initialized with 15 and fill mode is initialized as nearest.

Step 5: **Initialize Base Model**
In this step, VGG16 and InceptionV3 both types of models are initialized and the head of the model is excluded. After this, both head models are initialized with output of their base model. The average pooling has been applied of size 4×4.

Step 6: **Concatenation of models**
Both the head models of VGG16 and InceptionV3 are concatenated by using the Concatenate() method. This concatenation helps to improve the results.

Step 7: **Preparation of Head Model**
Now, the head of the concatenated model is prepared by doing some operation as shown below:

(a) Initially, the head of this model is flattened.
(b) Now a dense layer of 64 number of units is applied on this and these units affect output layers as well as the 'relu' activation function also applied.
(c) After this, 0.5 dropout is applied on the input to suppress the overfitting.
(d) In the last step, a dense layer of 2 units is applied with a softmax activation function because of classification problems.

After going through all of the steps mentioned above, the head of the model is ready to implement on the top of the base model. Thereafter, the head of the model on the top of the base model of the concatenation model is placed and the model is ready for training.

Step 8: **Compile the Model**
In this step, the proposed model is compiled with 'adam' optimizer with a learning rate 0.001, loss selected as binary cross-entropy. Adam optimizer is the combination of AdaGrad and RMSProp algorithm which provides better optimization of noisy data [18].

Step 9: **Train the Model**
In this step, the model is trained on 80% of the dataset with 25 numbers of epochs and batch size is selected as 32.

Step 10: **Test the Model**
In the end, the model is tested on the remaining 20% of the dataset and results are

achieved. Most of the results are achieved by confusion matrix, such as accuracy, precision, recall, F1-score, sensitivity, and specificity.

4 Results and Discussion

This section discusses the dataset, performance measures and results obtained from the proposed approach and other approaches.

4.1 Datasets Used

In this paper, chest X-rays images of normal as well as COVID infected patients are used from publicly available datasets. These datasets are taken from Kaggle [16] and GitHub [17], respectively. From these datasets, 720 X-rays images have been trained and tested on this model. In 720 X-rays images, 540 X-rays images for normal persons and 180 X-rays for COVID-19 infected persons. 80% of this dataset has been trained on this model, whereas 20% tested on this model. As the X-rays images are available of different persons and not uniform in size. So, all X-rays images are resized of 224×224. As the size of the dataset is less, the model supposed to perform well for this augmentation applied on the dataset thereby resulting in improved accuracy as well as other metrics. For augmentation, rotation-range is chosen as '15', and fill mode is chosen as 'nearest'.

4.2 Performance Measures

Though this dataset is balanced, still depending on accuracy alone is not enough for an optimal classifier. So, by using a confusion matrix, all other metrics such as Precision, Recall, F1-measure, Sensitivity, and Specificity are calculated. These four metrics are widely used in machine learning to the analysis of classification [19]. A confusion matrix introduces four terms such as True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), which can be used to solve the values of above metrics.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$F1 - Measure = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN} \tag{5}$$

4.3 Performance Evaluation

The predicted outcomes of the proposed ensemble model and confusion matrix are shown in above Table 1. The accuracy obtained from VGG19+IncpetionV3 is highest among the other ensemble models. The accuracies achieved from VGG+IncpetionV3 and VGG19+ResNet50 are 99.31% and 98.61%, respectively. The performance of VGG19+IncpetionV3 is better than the other ensemble models in terms of sensitivity, specificity, precision, recall and F1-Measure.

Fig. 2 shows the confusion matrix of each transfer learning model. '0' shows here Covid and '1' denotes here Normal.

The model is trained on 25 epochs with learning rate 0.001 and 'adam' optimizer. By this loss and accuracy graphs are plotted as shown in Figs. 3-6.

An ROC (Receiver Operating Characteristics) curve is used to show the performance of the classification models. To plot this graph, basically two parameters are used such as True Positive Rate and False Positive Rate. For each individual and ensemble pre-trained model the ROC curve can be shown below Fig. 7.

5 Conclusion

In this paper, an ensemble model is developed by using a combination of VGG16 and InceptionV3 to get better accuracy and other results. VGG16 and InceptionV3 are part of the pre-trained model. The benefit of pre-trained and transfer learning models was that it was not implemented from scratch, rather, it used previously collected knowledge and applied to different datasets. For this paper, the dataset used was consisting of 720 X-rays images of COVID and normal people. The proposed model was trained on 80% of the dataset and the remaining 20% was used to test the model. By this model, we achieved an accuracy of about 99.31% and also a confusion matrix. By using confusion matrix, all other metrics such as precision,

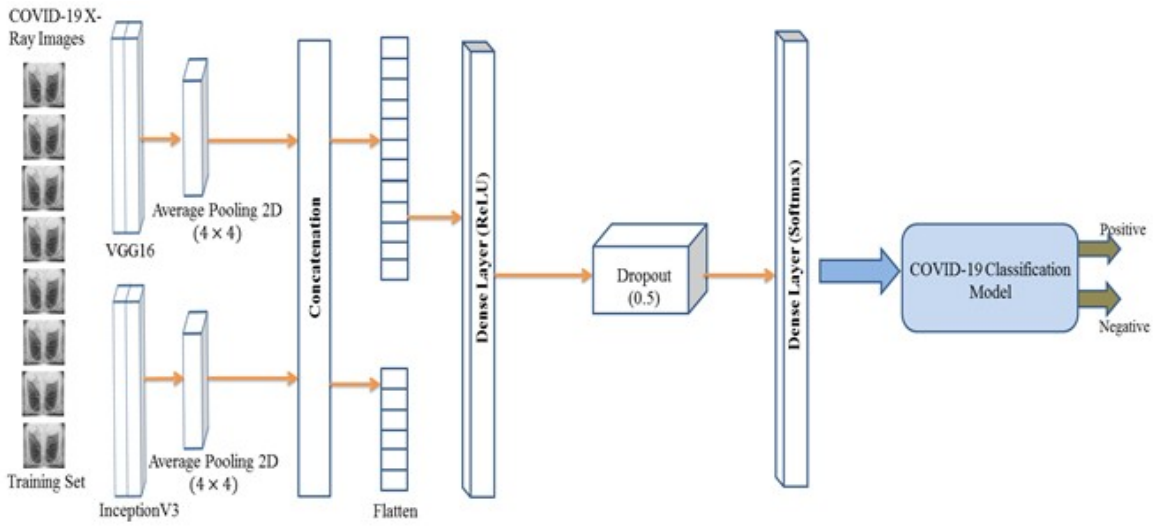

Fig. 1 Proposed Ensemble Deep Learning Architecture

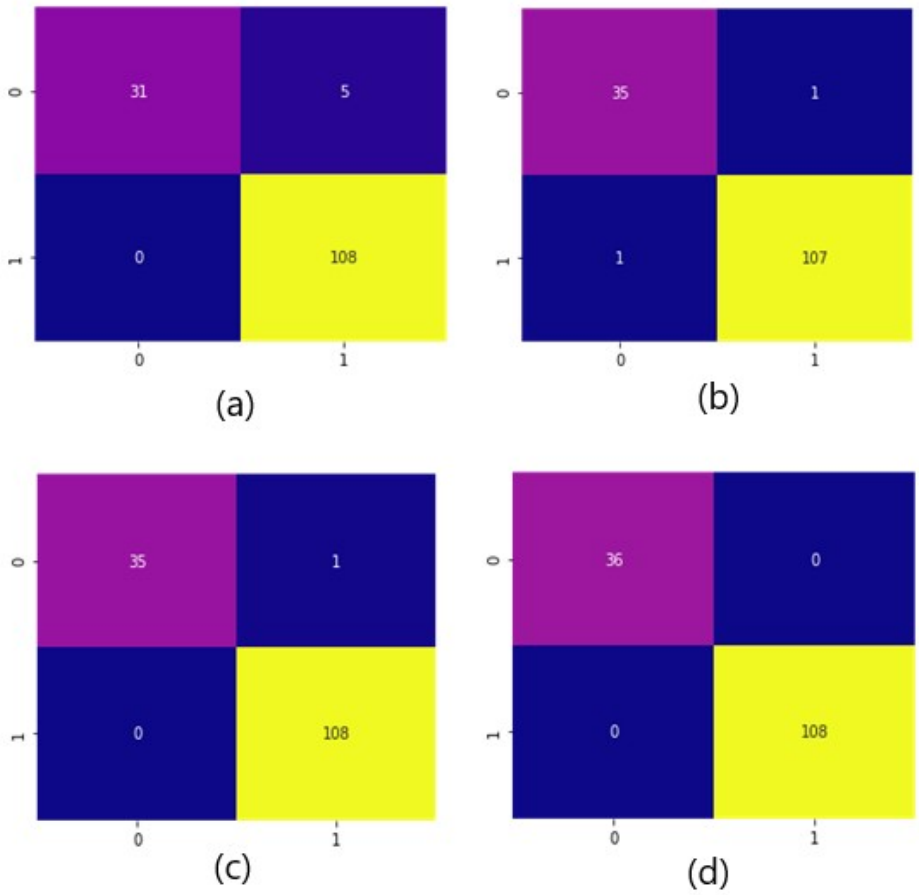

Fig. 2 Confusion matrix of different ensemble transfer model (a) VGG19+ResNet50, (b) VGG16+ResNet50, (c) VGG16+InceptionV3, (d) VGG19+InceptionV3

Table 1 Results obtained from each proposed ensemble model for COVID-19 classification.

Model	Accuracy	Precision	Recall	F1-Measure	Sensitivity	Specificity
VGG16	0.8	0.8	0.8	0.8	0.81	0.82
VGG19	0.6	0.5	0.625	0.55	0.54	0.55
ResNet50	0.5	0.39	0.38	0.5	0.42	0.43
InceptionV3	0.59	0.589	0.567	0.72	0.67	0.69
VGG19+ResNet50	0.9653	1.00	0.86	0.93	0.8611	1.00
VGG16+ResNet50	0.9861	0.97	0.97	0.97	0.9722	1.00
VGG16+InceptionV3	0.9931	1.00	0.97	0.99	0.9722	1.00
VGG19+InceptionV3	1.0000	1.00	1.00	1.00	1.00	1.00

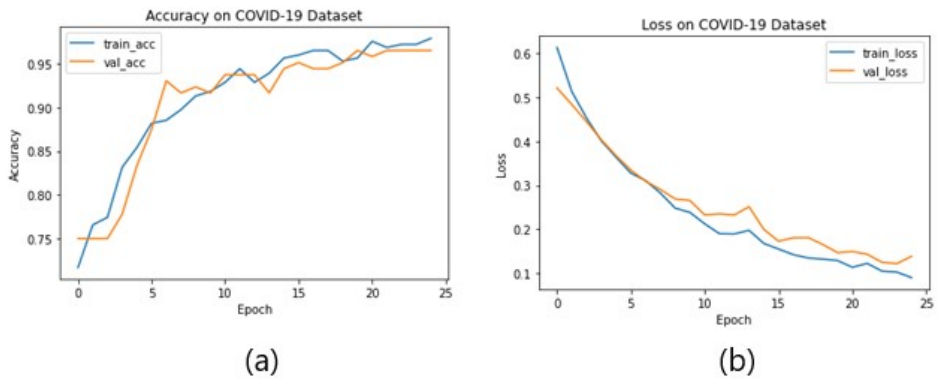

Fig. 3 Graph of Ensemble VGG19+ResNet50 (a) Accuracy, (b) Loss

recall, F1-score, sensitivity, and specificity were calculated that helped plot the loss and accuracy graphs. This dataset was of a limited number of images. So, by increasing the X-ray images, the data augmentation techniques should be used. By ensemble and increasing the dataset not only accuracy as well as some other results such as precision, recall, F1-score, sensitivity, and specificity can be increased.

Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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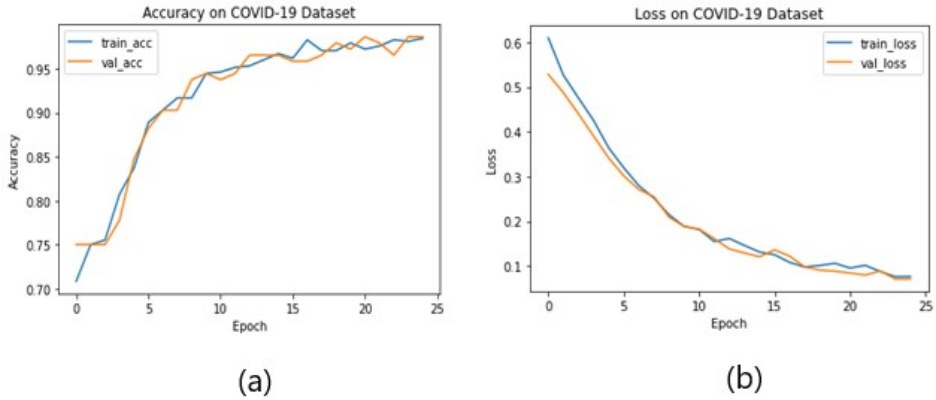

Fig. 4 Graph of Ensemble VGG16+ResNet50 (a) Accuracy, (b) Loss

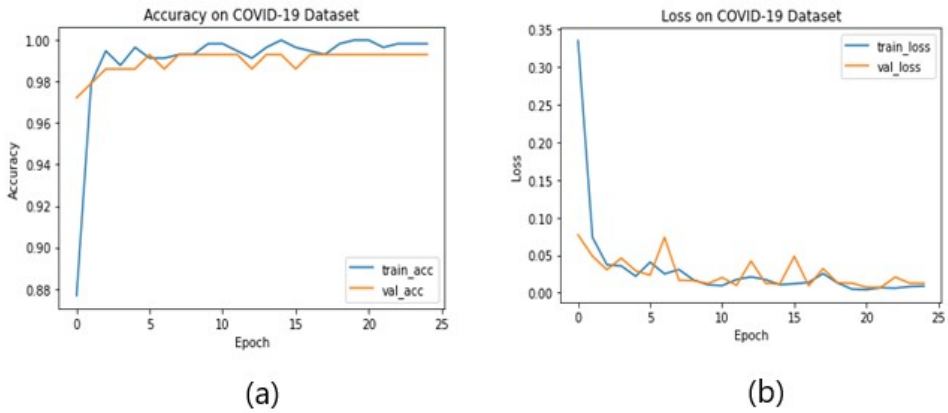

Fig. 5 Graph of Ensemble VGG16+InceptionV3 (a) Accuracy, (b) Loss

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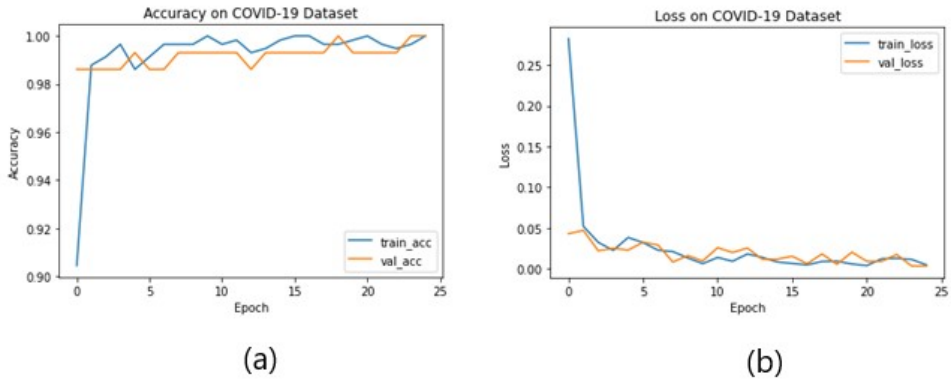

Fig. 6 Graph of Ensemble VGG19+InceptionV3 (a) Accuracy, (b) Loss

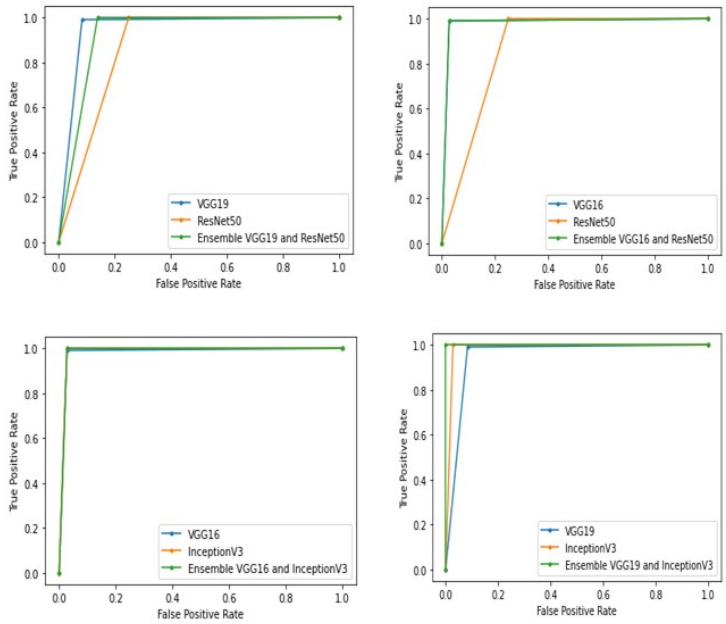

Fig. 7 ROC Curves Obtained by Ensemble Proposed Models

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