Deep Learning Model for Automatic Detection of COVID-19 by using CT-scan images

Abstract: The DNN model is implemented for the automatic detection of various kinds of diseases and abnormalities in different image modalities. Automatic detection of COVID-19 based on DNN models are utilized in this work, along with the four distinct image processing models namely, convolution neural network, VGG-19, Inception, and Xception are applied on publicly available 402 COVID-19 infected and 397 normal images of lung CT-scan images. A total of eight different gradient-based features are also extracted to train the traditional machine learning models. The Classification metrics of the deep learning model is also juxtaposed with machine learning models. The highest 93.887% and 94.092% training and testing accuracy has been achieved by applying the VGG-19 based deep learning model. The Image Processing models outperform the traditional DNN model. The research proposes a novel approach which is over-fitting independent and show accurate classification of covid-19 infection from normal diseases like Pneumonia using CT-Scan images of lungs.

Keywords: COVID-19; Image Processing; VGG-19; Inception; Convolutional Neural Network; Machine learning.

Declarations:

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Conflict of Interest/Competing Interests: No

Availability of Data and Material: Yes

1. Introduction

Coronavirus disease is a global pandemic which initially spread from Wuhan, China, in 2019. Now, COVID-19 has become the most dangerous disease all over the world. Total 192,788, 882 corona virus-infected cases with 4,141,891 death cases are reported worldwide from November 2019 to July 2021. While, In India, a total of 31,256,839 cases with 419,021 deaths were reported. On 13th January 2020, the initial case of Coronavirus disease was registered outside China, and the WHO characterized the disease as a pandemic on 11th March 2020. As of 22nd July 2021, around 200 million cases have been confirmed, with more than 4 million deaths across 224 countries, making the coronavirus pandemic one of the worst pandemics recorded in human history.

A coronavirus usually cause an infection in the sinus, nose, or upper throat. While, most coronaviruses are benign, but the SARS-CoV-2, causes respiratory tract infection and can eventually infect the lungs. The infection may trigger respiratory heart problems, failure, pneumonia, septic shock, liver problems, and death, making COVID-19 a severe threat to humans.

There are different types of coronavirus tests in practice. The most common one is the RT-PCR test, in which a special swab is used to collect samples from the throat and nose to direct detection of the virus. The Rapid diagnostic test (RDT) of a sample helps to detect viral proteins, which is related to COVID-19, and ensuring a speedy and accurate diagnosis. This paper suggests a new method for tagging the COVID-19 infection by analyzing the images obtained from CT-scan images of a patient’s lungs. Deep learning-based convolution neural network (CNN), VGG-19, Inception, and Xception based techniques are implemented to detect COVID-19 automatically. Machine learning algorithms such as K-NN, Logistic regression are also applied to analyze the results of DNN models.

The research is structured in following sections: the literature review is discussed in **Section 2.**, Materials and methods have been discussed in **Section 3**., **Section 4** includes the experimental results and **Section 5** encompasses the conclusions.

2. Literature Review

Mishra et al. used CNN model to detect COVID-19 from CT-scan images of chest [1]. The highest 86% accuracy is achieved with 88%, 86% AUROC, and F1-score, respectively. Wu et al. applied a DNN technique for segmentation and classification of COVID-19 by using images of lung CT-scan [2]. The highest 95% and 93% sensitivity and specificity have been achieved, respectively. Wang et al. utilized a DNN approach on images of CT-scan to detect COVID-19 infection [3]. Multitasking deep learning model is applied by Amyar et al. for segmentation and tagging of COVID-19 lesions via images of CT-scan. The highest 0.78 and 93% of dice coefficient and AUC has achieved, respectively [4]. Polsinelli achieved 85% accuracy by applying SqueezeNet based lightweight Image Processing model to identify COVID-19 infected with normal, and pneumonia infected images of CT-scan [5]. Jaiswal et al. used deep learning with DenseNet201 for the classification of COVID-19 infected with normal CT-scan images. The highest 96.25% accuracy is achieved with 2492 CT-Scan images of SARS-CoV-2 data set [6]. Deep transfer learning approach to detect COVID-19 using images of CT-scan is employed by Pathak et al. [7]. The highest 96.26% and 93.01%, training and testing accuracy is achieved with this model. Automatic segmentation and detection of SARS-CoV-2 infected regions based on the deep learning approach on CT-scan image is employed by Shan et al. [8]. Barstugan et al. extracted various features from chest CT-scan images [9]. The highest 99.68% accuracy is achieved having 10-fold cross verification technique and SVM classifier. Asnaoui et al. applied various DNN models for detection and classification of bacterial pneumonia, viral pneumonia, and coronavirus [10]. Yang et al. used DNN based CSSL model to detect COVID-19 [11]. The combination of 349 COVID-19 lung and segmented COVID-19 lung images of CT-scan are used for both training and testing. Highest 91%, 98.1%, and 89% F1-score accuracy, and the area under the curve, achieved, respectively.

The Contribution of this work

In the present work, three different deep learning-based models have been applied for the automated classification of COVID-19 by using images of lung CT-scan [11]. The dataset comprises of 402 COVID-19 infected and 397 normal images of CT-scan. Augmentation techniques are also applied on original images of dataset to implement a robust DNN training model. Sequences of experiments are analysed to assess the efficacy of the proposed model. The classification output is assessed in metrics of F1-score, accuracy, specificity, sensitivity, recall, precision, and area under the curve.

The proposed automatic COVID-19 detection system is ready-to-use, gives fast and accurate results using various deep learning-based architecture for large scale processing of data can be performed rapidly. Output shows the efficacy of the proposed method with rotated, scaled, and contrast varied COVID-19 test images to prove its robustness. The test output of the methods are juxtaposed with traditional supervised machine learning model which give comparable results to bolster the efficiency of research.

3. Proposed Methodology

The system for the automatic detection of COVID-19 consists of raw image acquisition, pre-processing, training of various deep learning models, and testing of the model. The architecture diagram of the proposed system is depicted in Fig.1. The precise description of every step is provided in the subsequent subsection.

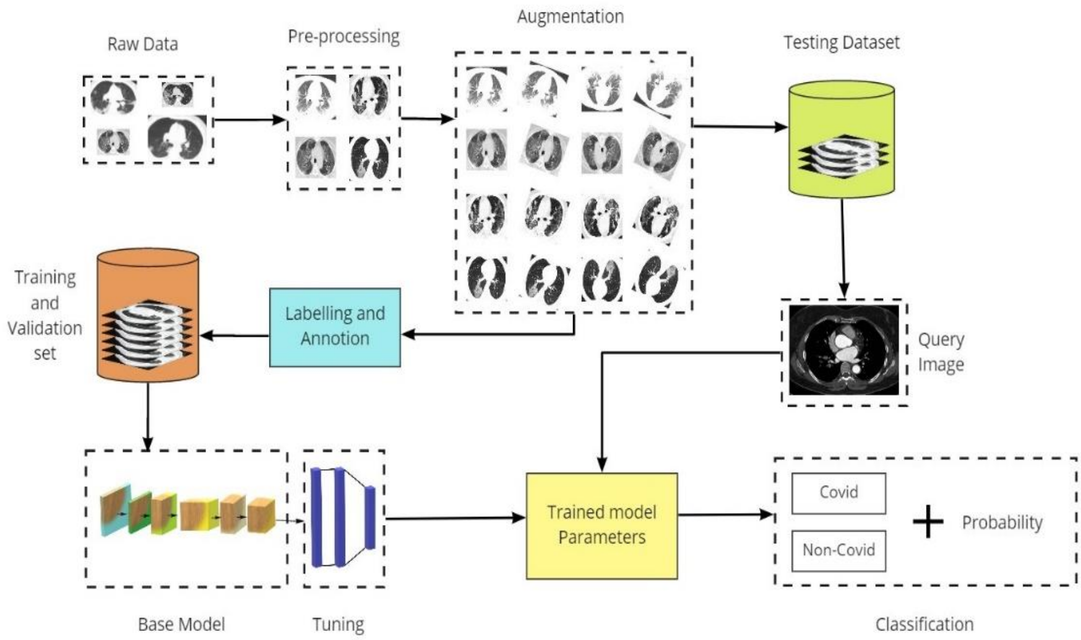


Fig 1. The Architecture diagram of the Proposed Deep Learning for the Detection of COVID-19

3.1 Data set Collection

Publicly available images of lung CT-scan are collected for the experiment and bolster the proposed model [11]. Data set utilized in the research consists of 402 COVID-19 infected and 397 normal images of lung CT-scan images. These images of lung are taken from 216 different COVID positive and 398 normal patients. Sample COVID-19 infected CT-scan images of a patient are depicted in Fig. 2 and Fig. 3 which are taken in 8 days continuously starting from the first day of treatment.

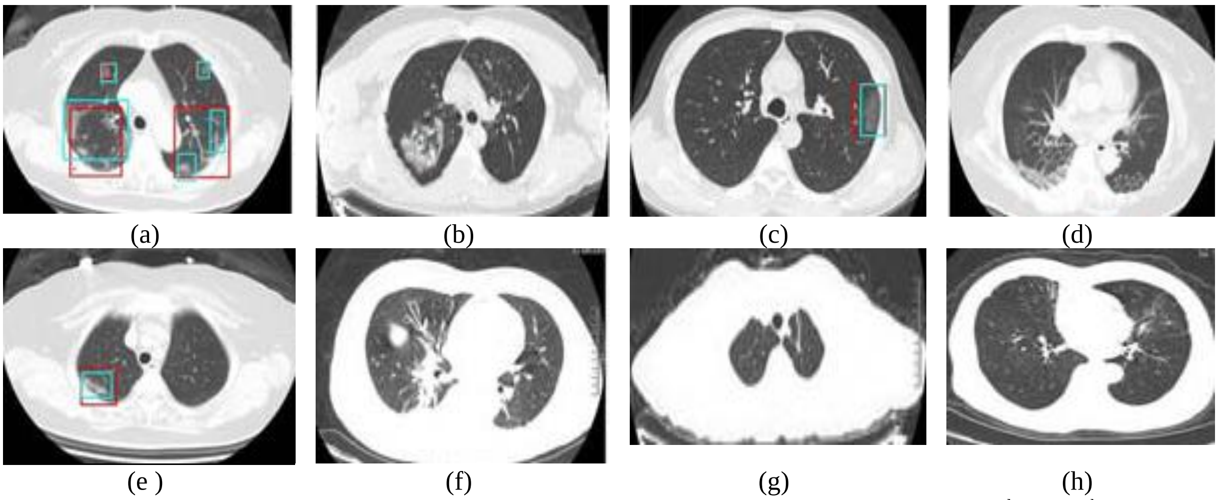
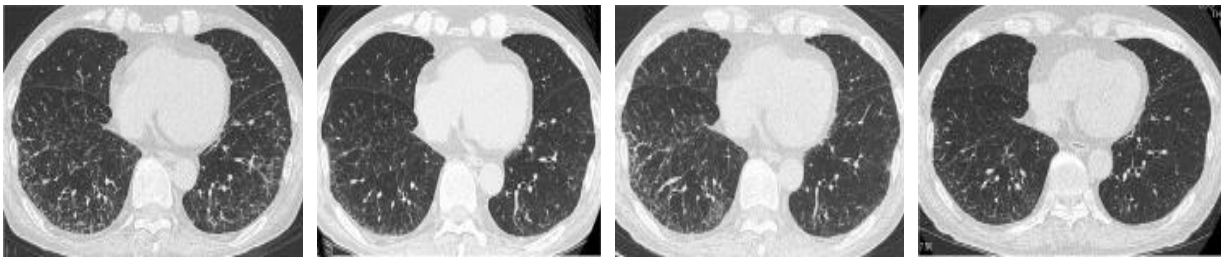


Fig. 2. CT-scan images of the SARS-CoV-2 infected patient taken from (a) 1^{st} day (b)-(h) 2^{nd} day- 7^{th} day, respectively



(a) (b) (c) (d)

Fig. 3. CT-scan images of the non-SARS-CoV-2 infected person taken from taken from (a)-(d) 1st day-4th day respectively

3.2 Pre-processing

The image pre-processing steps includes resizing image and contrast enhancement. The dimension of the resized images depends upon the number of input layers in the deep learning model. Further, the image augmentation technique is applied to generate a greater number of images as the limited numbers of images are available in the dataset. The over-fitting problems can be restrained and robustness of the model can also be proved by augmentation technique. Various augmentation techniques such as rotation, shearing, scaling, shift, and flip are used to generate new images. Efficiency of the test images can also be increased by using its different orientation.

3.3 Deep Learning Model

First, the dataset is split into validation, training, and testing set. After that, the training dataset is utilized for training the deep learning-based model. Weights of the training model can be fine-tuned with the validation set. Finally, the trained model is evaluated with the images of test dataset and analyse the performance of the model.

3.3.1. CNN model

Deep learning-based convolution neural network is already applied to detect object, semantic segmentation, and classification. Alexnet, Res-net, LeNet, GoogLeNet, VGGNets are some of the examples of CNN [12-14]. All CNN models consist of different convolutional, pooling to create a fully connected layer. CNN performs the various functions which are feature extraction, region identification, and its classification. Further, convolution, pooling, followed by connected layers are used to classify the COVID-19. The convolution layers are the principal component of the CNN model which consists of numerous convolutional kernels which generates the feature maps of input lungs CT-scan images for training of the network. Maximum value for the sliding window is given by the max pooling layer. Number of parameters depends on the structure of CNN model. The convolution kernel function transfers the input image to compute the kernel value.

3.3.2 VGG-19 Model

One more deep learning-based model which is VGG-19 is also used to detect COVID-19 in this research [14]. The architecture of VGG-19 model is shown in Fig. 4. The architecture of VGG-19 has total of 19 convolutional layers with approximately 144 million of trainable parameters. The final layer of the network gives the classification output and all previous layer extract features. 3×3 kernels with padding and stride of 1 are used in a convolutional layer to extract the features and generate activation maps. First two layers have 4096 ReLU activated units and the last one has 1000 softmax activated functions. The training network can converge in a small number of training epochs due to small kernel size. Over-fitting problems due the training with the small data set can be avoided with dropout layers. The preceding layers provides the probability for the classification to the final layer.

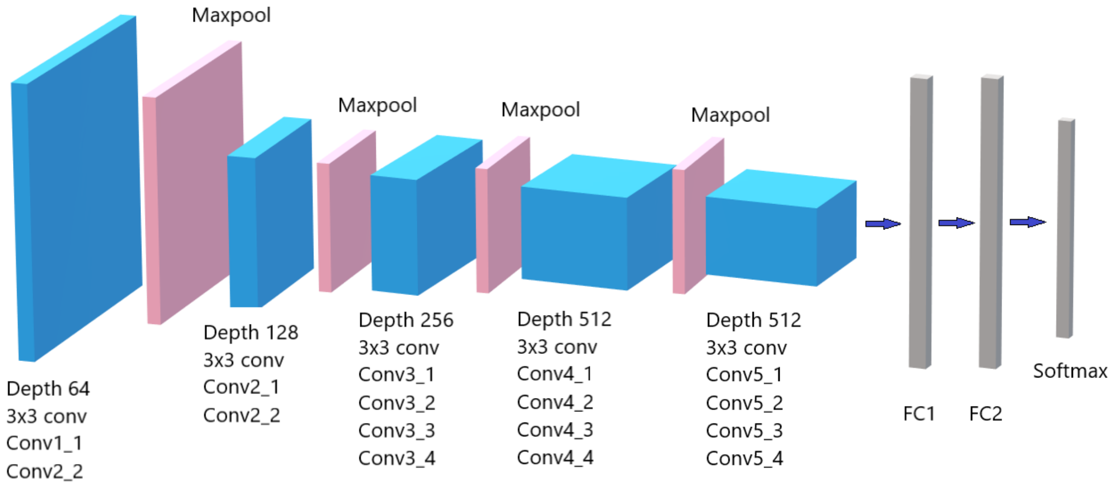


Fig 4. Architecture of VGG-19 Model

3.3.3 Inception and Xception Model

There are two additional CNN models, Inception and Xception are also utilised in this detection system [15]. The architecture of inception model is presented in Fig. 5.

An Inception module calculates many processes in parallel for the same input grid then combines the output into a unit result. Inception comprises a 5x5 convolutional transformation and a 3x3 max-pool for each layer. In the inception model, a layer is broken into 1x1 convolution, 3x3 max-pooling, 3x3 convolution, and 5x5 convolution. The computation by inception module is visualized in Fig. 5. Naïve and reduced dimension inception model is presented in the Fig. 6.

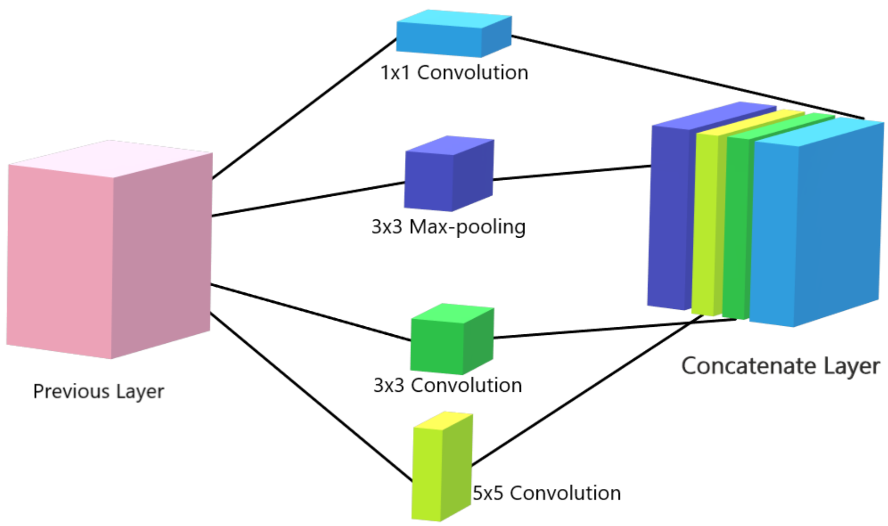


Fig 5. Architecture of Inception Module

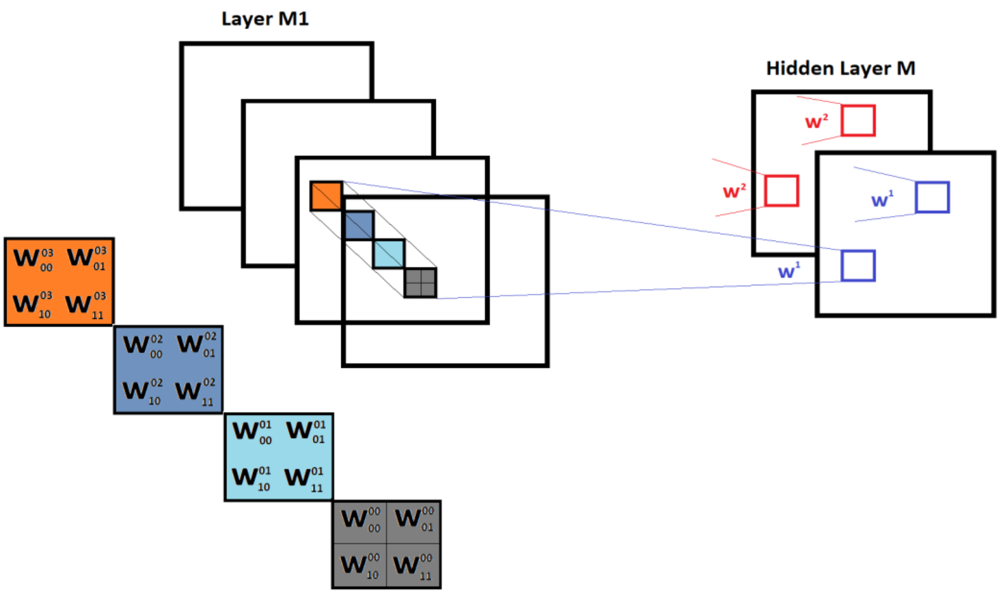


Fig 6. Computation visualisation of inception model

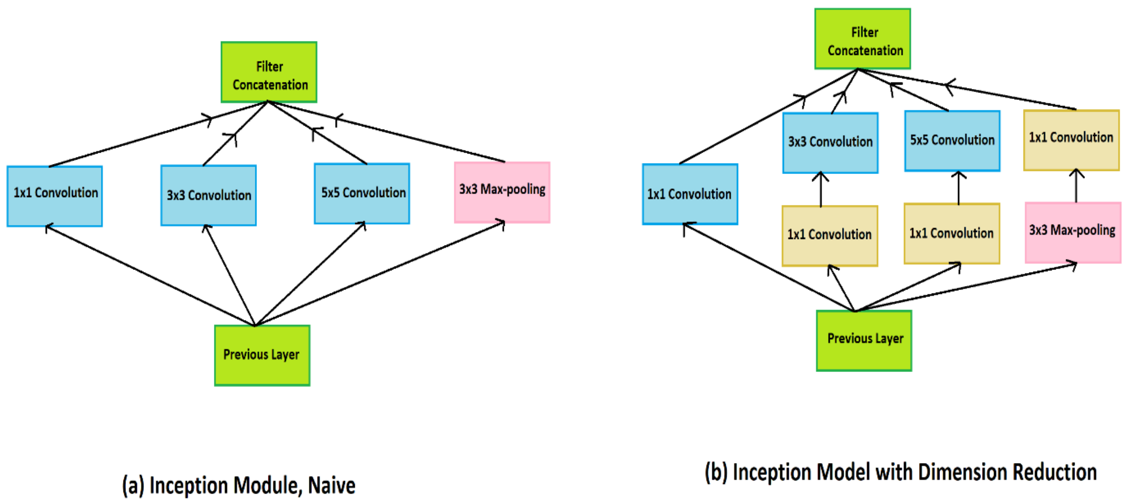


Fig 7. Architecture of (a) Inception Module and (b) Dimension Reduction

In Inception, 1x1 convolution is used to depict the initial input into several separate, diminished input spaces. Distinct types of filter are used to process the input spaces into the smaller 3-D block of data. Xception correlates the spatial connections for every output channel individually, after that, it applies a 1x1 deep convolution to resolve the cross-channel correlation as depicted in Fig. 7. The structure of Xception deep learning model is shown in Fig. 8.

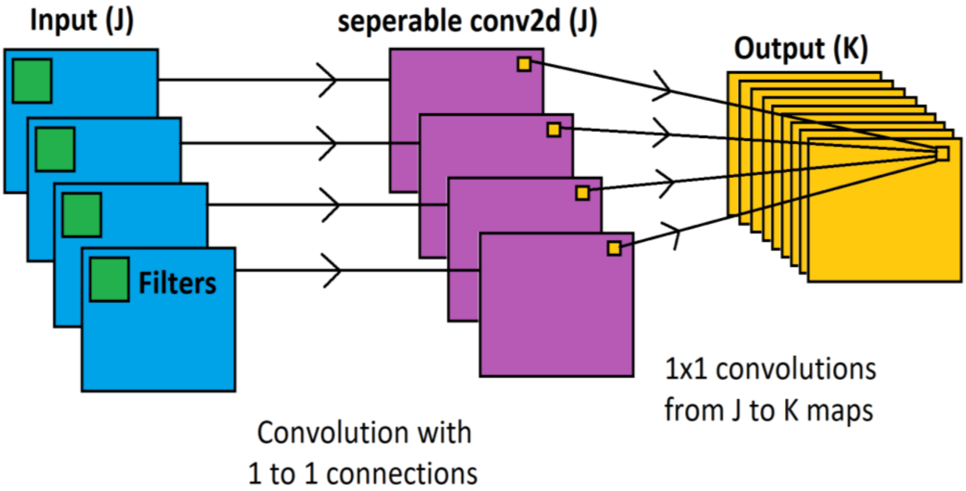


Fig 8. Architecture of Xception deep learning Model

4. Experimental Results and Discussions

Training of the deep learning model is performed with different CT-Scan lung images in the system having Intel processor, 128 GB RAM, GPU with 24 GB memory. The hardware and software configurations of the training system are given in Table I.

Table I. Hardware and Software Configuration used for the Experiment

Parameter Name	**Value**
Operating System	Windows 10, 64 bit
Processor	Intel (R) Core(TM) i7-8750H CPU @ 2.20GHz 2.21GHz
Installed RAM	8 GB
Graphics	NVIDIA GeForce GTX 1050 Ti
Graphics Memory	2782 MB
Development Environment	Anaconda, Jupyter Notebook
Programming Language	Python

Total 402 images of SARS-CoV-2 infected and 397 normal images of CT-scan have taken for training and testing of the various deep learning models are shown in table II.

Table II Number of CT-scan images

Number of CT-scan images taken	**COVID infected**	**Non COVID**

Training images	281	278
Testing images	121	119
Total images	402	397

Training of CNN, VGG-19, inception, and exception deep learning model has been done with 70% images of training data set. The CNN layer is trained with the input layer of 256×256 dimensions, six convolution layers, and two max pool layers. The evaluation of the proposed Image Processing models and the DNN model is measured in terms of specificity, sensitivity, precision, accuracy, recall, and F1-score. The Classification evaluation is determined via a confusion matrix. The two classes are predicted output that can be categorized in four possibilities. The model predicts as non-COVID or outcome is predicted as 0 and the model predicts as COVID-19 or outcome is predicted as 1. Various deep learning models have the different number of layers and parameters. The numbers of epochs and training time are also varied for different models which are presented in Table III.

Table III Various Parameters used in Different Deep Learning Models

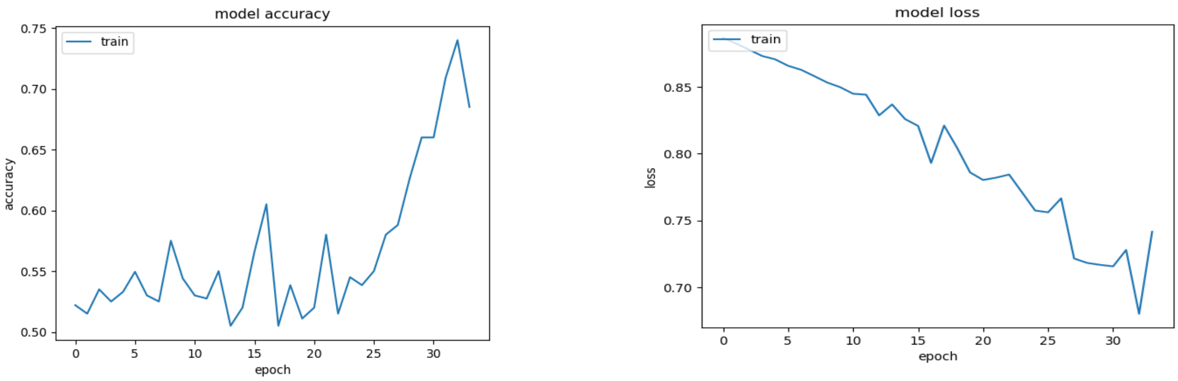
Deep Learning Model	**Input Size**	**Number of Parameters**	**Number of Training Epochs**	**Batch Size**	**Training Time**
CNN Model	300×300×3	18,090,135	34	50	1169s
VGG-19	224×224×3	20,074,562	50	32	6667s
Xception	224×224×3	22,961,706	16, 8	5, 50	29361s
Inception	224×224×3	23,903,010	16, 8	12, 12	4603s

The outcome of all the proposed deep learning models is shown in Table IV. It can be analysed from the results that from the results that the VGG-19 produced the highest testing accuracy of 93.87% and training accuracy of 94.76%. The accuracy and model loss graph of each deep learning technique is shown in Fig. 9.

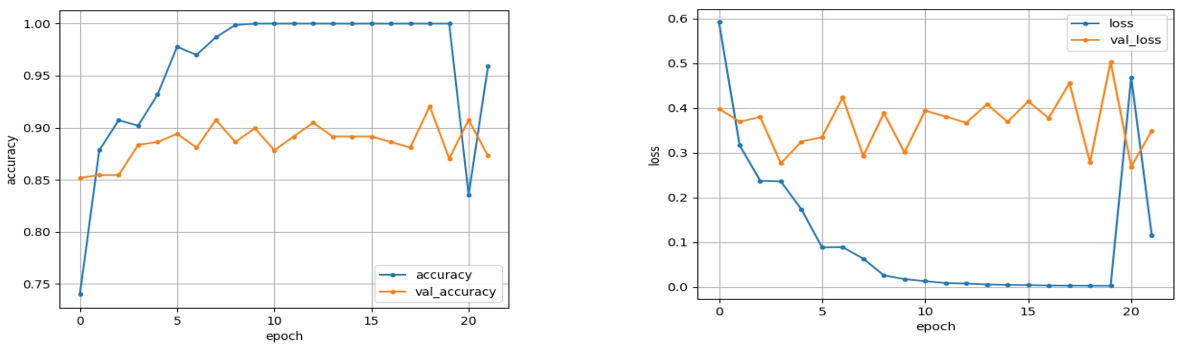
Table IV Result Obtained with the Various Image Processing Models

Technique Name	**Sensitivity**	**Specificity**	**Precision**	**F1-Score**	**Recall**	**Training Accuracy**	**Testing Accuracy**
CNN model	100	86	75	26	100	70.172	72.197
VGG-19 model	**97**	**91**	**96**	**96**	**95**	**93.887**	**94.092**
Inception model	97	84	93	95	97	91.028	93.450

Xception model	99	73	89	94	99	88.074	90.830



(a)



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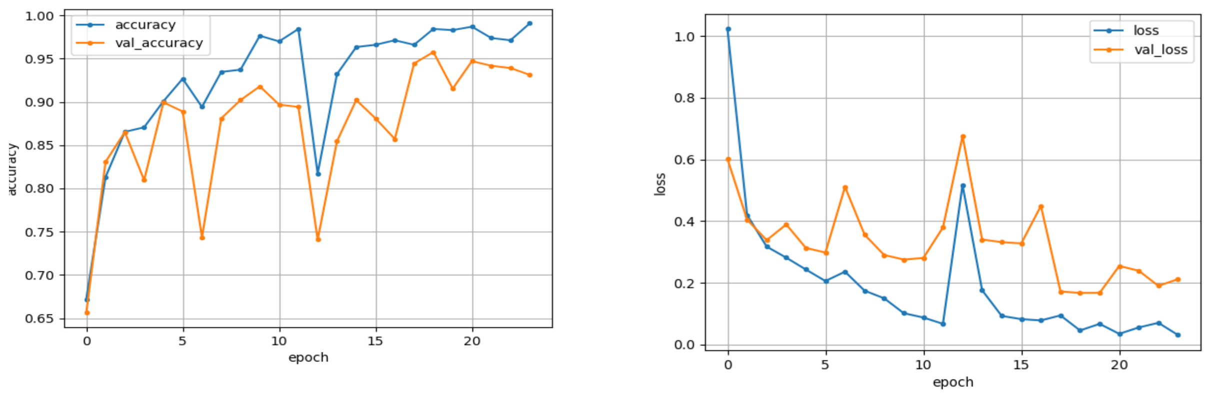

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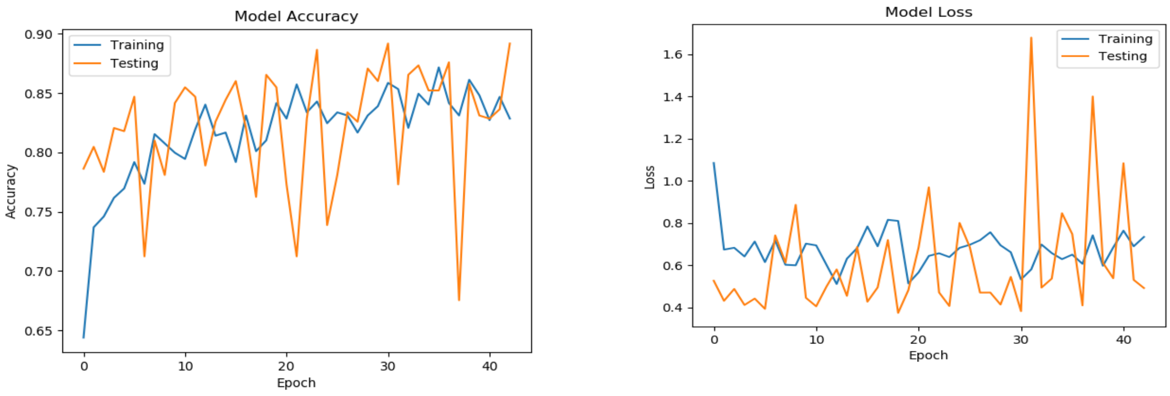


(d)

Fig. 9. Model accuracy and model loss (a) CNN model (b) Xception Model (c) Inception, and (d) VGG-19 Model

4.1 Comparison with Machine Learning Techniques

Total eight different gradient-based features are also extracted for the training and testing of various traditional machine learning models, namely, support vector machine, the artificial neural network, random forest, and K-NN (with K= 3, 4, 5, and 6). The brief description of each feature is presented as:

1) STD_IMG: Measures the dispersion of a dataset relative to its mean is calculated using the Standard deviation of all the pixelated values of the image.
2) Unique_clrs: It represents the total number of unique values of pixel colours in the image.
3) ABS_Mean_x: the absolute average of x-direction gradient or horizontal gradient values of the image, which is calculated using the SOBEL operator in (1, 0) mode or in horizontal direction vector.
4) ABS_STD_x: representing the standard deviation of x-direction gradient or horizontal gradient values of the image, which is calculated using the SOBEL operator in (1, 0) mode or in horizontal direction vector.
5) ABS_Max_x: being the maximum value of x-direction gradient or horizontal gradient values of the image, which is calculated using the SOBEL operator in (1,0) mode or in horizontal direction vector.
6) ABS_Mean_y: being the absolute average of y-direction gradient or vertical gradient values of the image, which is calculated using the SOBEL operator in (0,1) mode or in vertical direction vector.
7) ABS_STD_y: representing the standard deviation of y-direction gradient or vertical gradient values of the image, which is calculated using the SOBEL operator in (0,1) mode or in vertical direction vector.
8) ABS_Max_y: being the maximum value of y-direction gradient or vertical gradient values of the image, which is calculated using the SOBEL operator in (0,1) mode or in vertical direction vector.

Sample values of the different features are demonstrated in Table V.

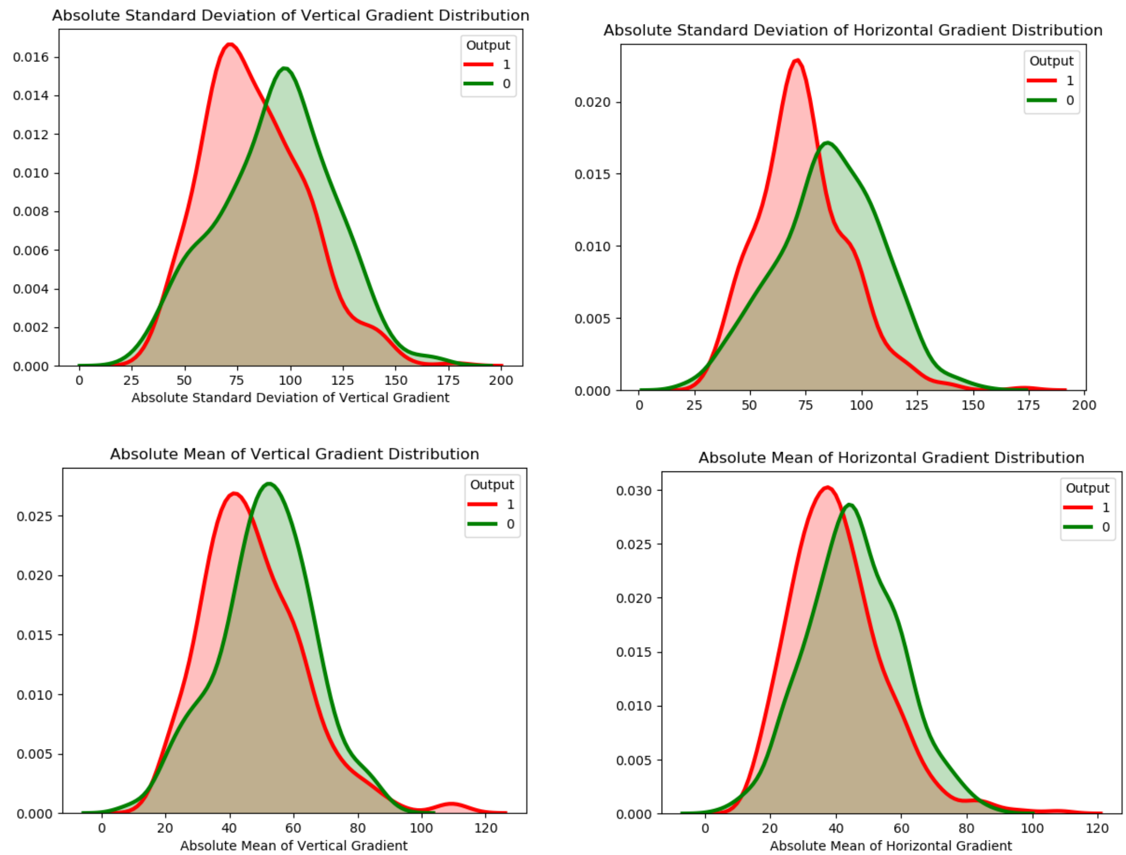
Table V Sample values of various features extracted from the dataset

STD_IMG	Unique_clrs	Mean_x	STD_x	Max_x	Mean_y	STD_y	Max_y
81.19	232	57.26	99.23	749	47.84	81.168	707
84.07	255	58.64	104.69	848	46.99	79.909	677
68.023	226	51.17	74.66	638	45.81	71.41	622
83.57	230	61.84	109.35	767	54.87	92.66	659
73.10	240	72.68	100.66	785	55.22	67.89	572
69.22	247	57.44	95.047	809	53.13	84.126	756
72.68	246	66.70	99.834	785	49.95	72.609	846
77.83	244	56.16	93.311	804	53.62	92.412	841
74.00	256	65.37	108.85	944	51.75	79.575	768
72.64	256	60.77	106.02	870	52.94	86.018	828

Numerical occurence of the column-wise information is depicted in Fig. 10 as a displot graph. It can be analyzed that from the plot that the occurrence of the numeric distribution that the difference is noticeable, and certain conspicuous conditions can be outlined to discern the COVID infection using extracted attributes.

The Fig. 11 depicts the correlation or the level of interdependence which is represented by the size of the square according to the entities in the row and column, respectively. The heat map of co-variance of attributes are shown in Fig. 12.

The various machine learning algorithm, namely KNN (for K=3, 4, 5, and 6), RF, and SVM. The comparison of training and testing accuracy of all Image Processing and DNN models are depicted in Fig. 13. The results obtained in terms of specificity, sensitivity, precision , F1-score and recall and Fig.14, respectively. The KNN3, KNN4, KNN5, and KNN6 produced a training accuracy of 87.83%, 84.21%, 81.58%, 81.58% respectively, and testing the accuracy of 68.42%, 68.42%, 68.42%, and 64.57% respectively. The accuracy of RF in training is 100% and testing is 78.51%. SVM has 82.57% training accuracy and 71.49% testing accuracy. ANN model with the Keras layer produced an accuracy of 97.37% in training and accuracy of 76.32% in testing. The combined ROC of all applied image processing and DNN models are depicted in Fig.15(a) and Fig. 15(b), respectively.



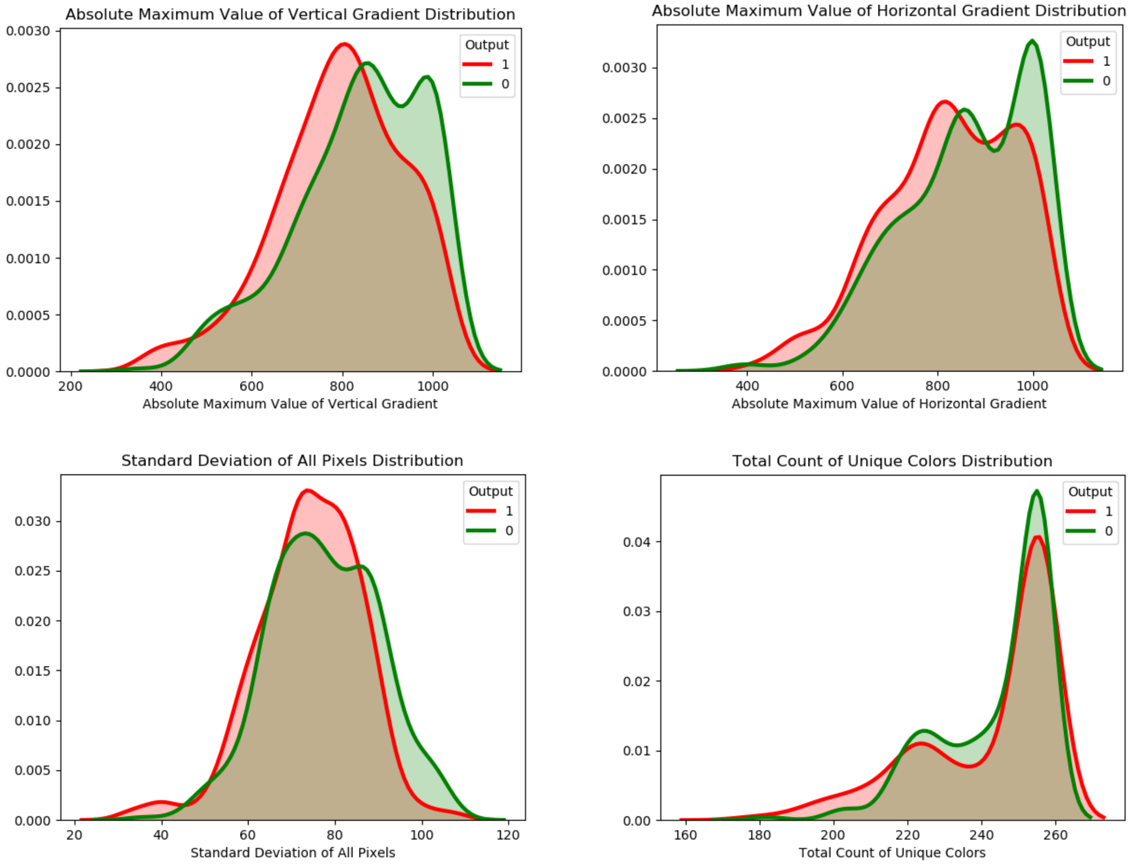


Fig 10. Numerical Distribution of Column-wise data in Displot Graph.

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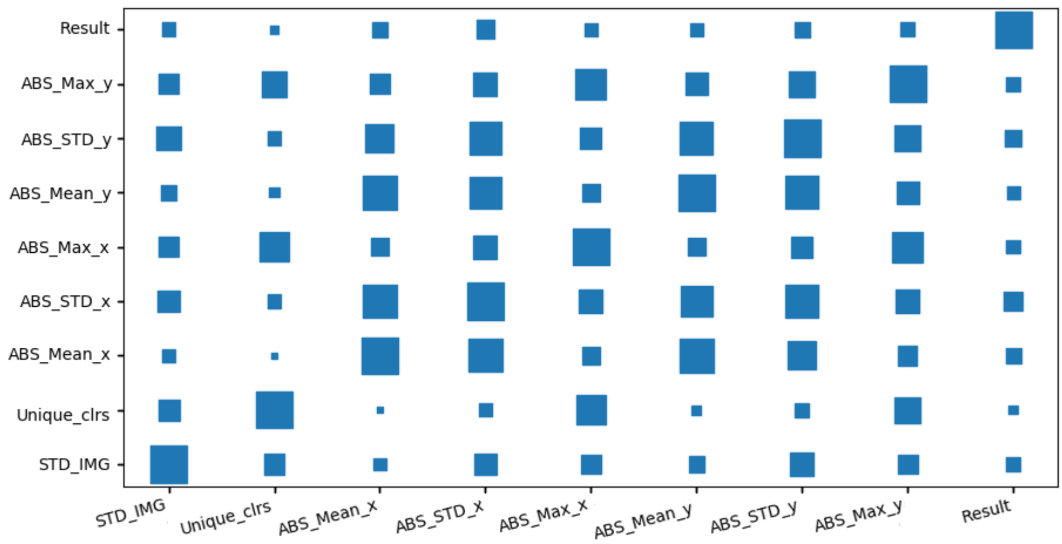

Fig 11. Attribute-to-Attribute Co-variance Size Scatterplot

Fig 12. Co-variance Heat-map

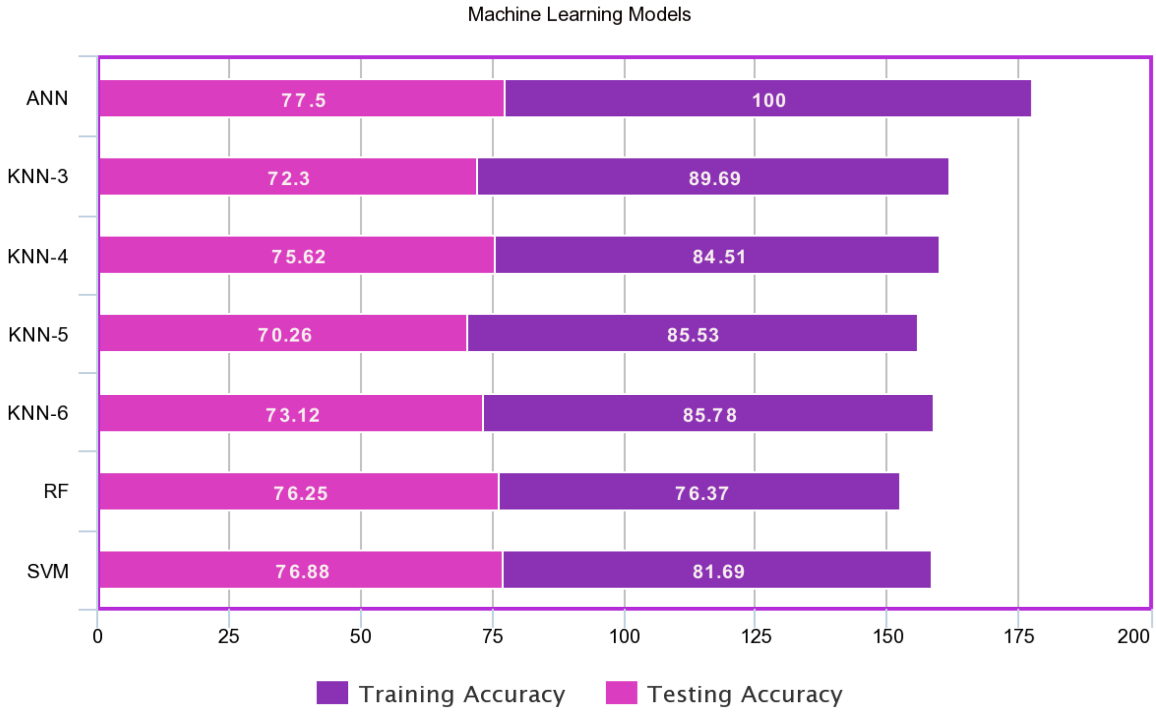

Fig 13. Comparison between testing and training accuracy of various machine learning.

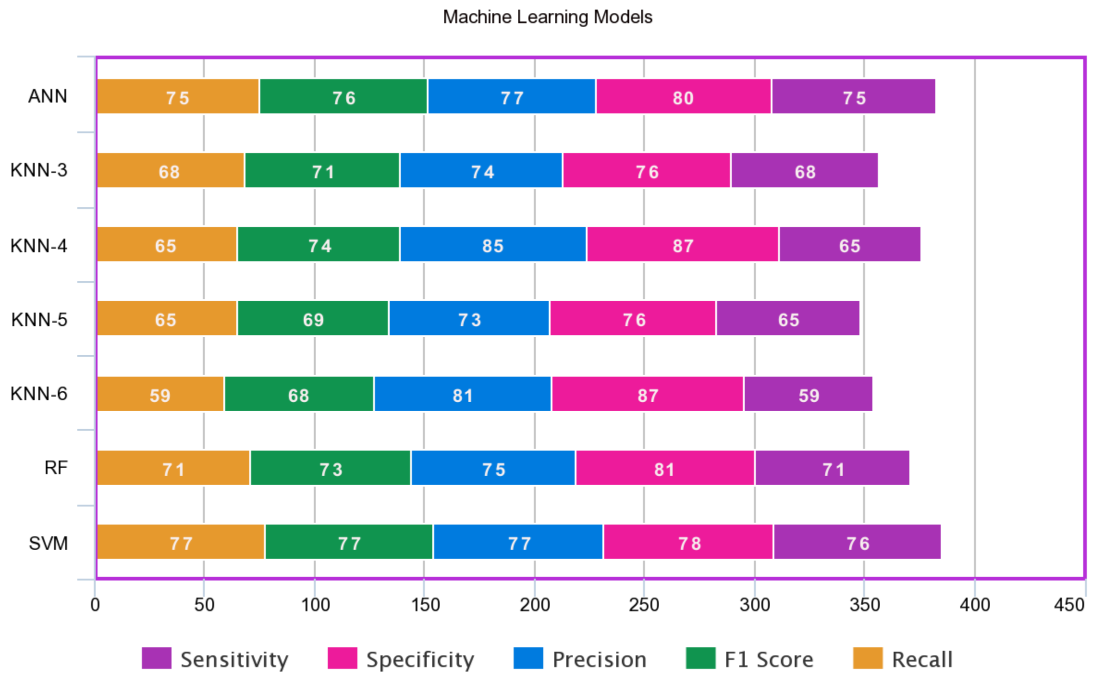

Fig 14. The Results Obtained with the various machine learning models on the basis of Sensitivity, Specificity, Precision, F1 score, and Recall.

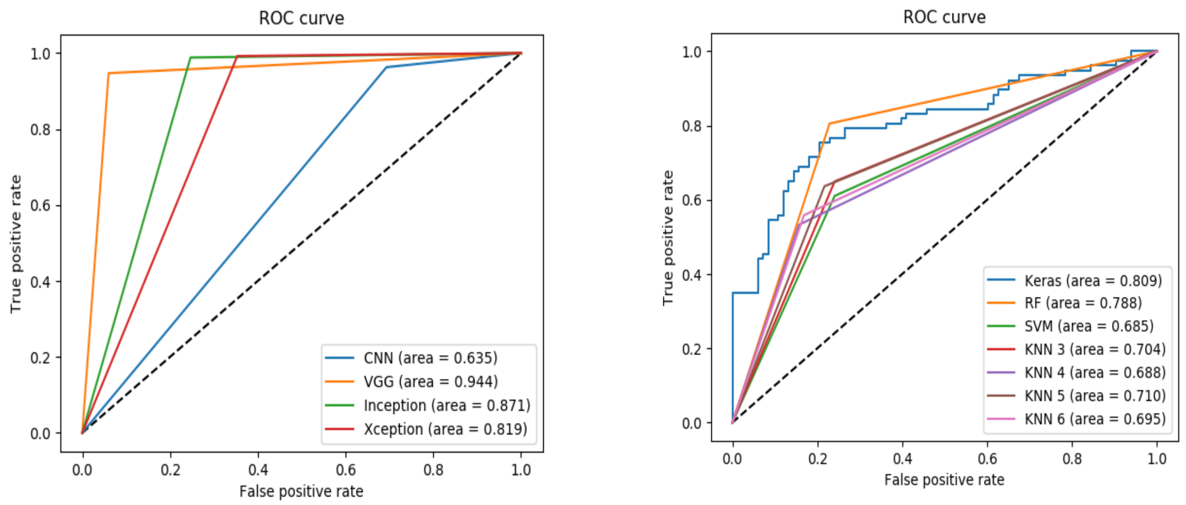

Fig 15. The Combined ROC of (a) Various Deep Learning Models, and (b) Machine learning models

In the presented work, it is observed that the best training accuracy of 93.89% and testing accuracy of 94.09% is obtained by detecting the presence of coronavirus disease in lung CT scan images.

5. Conclusions

This paper presents the deep learning based automated COVID-19 technique by utilizing lung CT-scan images. The four different DNN models are applied in this work. The CT-scan images of lungs are preprocessed and augmented for the better learning of the neural network and to avoid the over-fitting. The highest training and testing accuracy of 93.89% and 94.09% is achieved by the VGG-19 model. The various machine learning models are also trained based on 8 various gradient based features. The Image Processing models outperform the traditional machine learning techniques in terms of both training and testing accuracy. Further the model will be evaluated using new and enhanced datasets and the trained model will be deployed on the web application, so that people can avail a chance to access the model.

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Conflict of Interest

There is no conflict of interest

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