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Accurate COVID-19 Detection using Xception with X-ray Images

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ABSTRACT

The outbreak of coronavirus complaint is generally known as COVID-19. It has a major impact on human health and their routine life in various countries. Early discovery of COVID-19 through accurate detection and observation of the original point of infection in the case of COVID-19 is essential to control the disease and reduce its rapid-fire spreading among people worldwide. This helps to diminish the death rate. In the health care unit, primarily X-ray has been used to test the patients. The proposed system aimed at the structure of different trained Deep literacy models grounded on Convolutional Neural Networks (CNNs) for the spontaneous exposure of COVID-19 using X-rays. The ease of diagnosing the cases requires detecting the complaint from radiography images. The earlier studies on this content include machine literacy strategies for COVID-19 using casket X-rays showed good delicacy and discovery rate. Presently, the RTPCR test is the most generally used fashion to discover the complaint of COVID-19. But the major problem occurs when it has a high false rate, and the time for carrying the results is also high. In this research, we proposed a COVID-19 detection model using Deep Convolutional Neural network (DCNN) algorithms using the X-ray images. According to the research, it is found that Deep CNN models are producing the most accurate results for COVID-19 detection. The use of this DCNN model in analyzing X-ray images in the proposed model is producing 98% accurate results in finding COVID or Non-COVID.

Keywords: COVID-19; Confusion matrix; Deep neural network; False negatives; X-ray images

1. Introduction

According to the review by WHO, the COVID-19 virus is considered a most deadly disease and kills human life. Early detection of this virus can reduce the patient's death rate. As per the Government guidelines, the RT-

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PCR test is used in hospitals to test the novel coronavirus [1-3]. Professionals in the health care unit face challenges in detecting robust and accurate COVID-19. X-ray images in [1, 4] will help detect COVID-19 for its early treatment. COVID-19 outbreak has stretched out the healthcare systems globally as they dealt with a large number of cases. Since the X-rays are very fast, cheap, harmless, and easy to access they can help to identify patients affected with COVID-19 quickly. The system provides an efficiency greater than 95% and is automated with fewer efforts. RTPCR tests [2] predict false negatives and false positives due to the samples taken from the patients being tested in labs [1, 3]. Thus RT-PCR is not only a method that should be taken into consideration. because compared with false positives, false negatives cause tremendous spread worldwide. So, these days, technical professionals are attracted to DCNN models for detecting COVID-19, among the DCNN models transfer learning is one of the most common approaches used. The study was conducted by [1-3] on 610 Wuhan hospitalized patients who had been diagnosed with COVID-19. In this paper, it is found that the RT-PCR test produces high false-negative results. they also found the necessity of X-ray images and computed tomography (CT) images for the diagnosis of COVID-19. Most recent research conducted by [5] analyzes the results of CT scans and RT-PCR. This paper shows the diagnosis of COVID-19 effectively by analyzing the features of CT scan images. It is identified that chest CT scans are useful for those who have the symptoms of COVID-19 and negative RT-PCR results. Artificial Intelligence plays a key role in screening COVID- 19 due to the lack of facilities and radiologists available worldwide.

2. Related Work

The authors [1] took the aid of computer technology to detect COVID-19 since there are flaws in current COVID-19 detection mechanisms. For example, if we consider RTPCR and Rapid test, which have high false rates due to which many people across the globe may suffer. In order to give a more precise method of detecting COVID-19 utilizing chest X-Ray images, the researcher's goal was to review up to 200 X-ray chest images of COVID-19 patients as well as normal chest photos. CLAHE is a method that uses a histogram equalization approach to handle X-ray datasets and analyses the performance levels of CNN when used together. It enhances the caliber of categorized images to produce meaningful results. Along with the basic model of CNN, A transfer learning model-VGG16 is used. Because they used such a small amount of dataset, which was insufficient for the model's training and validation, the accuracy of VGG16 compared to the CNN basic model is poor, despite the fact that it should be high, according to the research's findings. Since almost all hospitals have an X-ray device this approach to COVID-19 virus detection may be used considering they now no longer want any unique kit. The authors of this research paper [6] had taken into consideration the factors like high variance, overfitting, and generalization errors with a limited number of datasets, which are not suitable for an accurate COVID-19 detection model. They have used datasets involving various chest X-rays and chest CT scan images as they have high sensitivity towards pulmonary diseases. to make predictions with multiple models instead of a single model they used the Ensemble Deep learning model, which had multiple combinations of deep learning models. However, here instead of training multiple deep learning models, they have generated different deep learning models using a single neural network that violates the model diversity required for ensemble learning and affects the model since the model accuracy depends on the diversity of these multiple deep learning models. Various models like Alex Net, COVID MT-NET, HSMA WOA, etc. are used in the main process of the deep learning model. The authors have used a dataset of around 15,477 chest X-Ray images for model training and evaluation containing three cases i.e., COVID-19 patient's X-ray images, Normal people X-ray images, and Pneumonia patient chest X-Ray images. The results show that this EDL-COVID can detect COVID-19 with good promising results of 96% sensitivity and with an accuracy of 95%.

The authors [7] used four models such as CNN, VGG16, VGG19, and InceptionV3, and the performance of each model is tested and found that VGG16 and VGG19 performed well as compared to other models. The data set is collected from universities and consists of images of COVID-19 positive patients, healthy patients, and chest radiographs of viral pneumonia patients. The data set includes chest X-ray images of a total of 657 images (219 COVID19 patients, 219 healthy patients, and 219 viral pneumonia patients). A total of 657 chest X-ray images have been examined for the diagnosis of COVID-19 using deep learning methods and found that VGG19 is the most successful and gives a higher accuracy rate of 95% while InceptionV3 is the maximum unsuccessful approach for a given dataset. The authors used the transfer learning model of ResNet-50 primarily making use of a pre-trained convolutional neural network on chest X-ray images. Data set created from different sources are the Italian Society of Medical and interventional Radiology (SIRM) provides statistical data set of Corona Virus open-supply, statistics set created through compiling recognized photos from articles, and Chest X-ray photos statistics set. Classification of COVID-19 cases was trained and tested using the ResNet-50 model and achieved 99.5% classification accuracy in [7] which can help in clinical practice and also be used in situations where possibilities of performing RT- PCR tests are insufficient and the availability of doctors is not sure. The research con- ducted by [5] has proposed a deep neural network-based system where the pro- posed CNN model has achieved 94.03% accuracy. The chest X-ray images of COVID-19 patients, pneumonia patients, and normal people were used to train the system. The chest X-ray images of COVID-19 patients, pneumonia patients, and normal people were used to train the system. The system was tested on only 285 photos, and this short sample size made it difficult to train a deep learning-based system for the COVID-19 prediction, according to [8].

Researchers have developed a transfer learning method (Xception model) in [9] using deep learning models for diagnosing COVID-19. The proposed method had an accuracy of 96.75% for COVID-19 diagnostics. To improve the accuracy and develop an efficient diagnostic model of the Xception model they have employed Deep features and machine learning classification. The authors have asserted that their proposed method has a higher classification accuracy and efficient performance for diagnosing COVID19. They did not, however, compare their findings to earlier, comparable investigations. The authors have used a pretrained deep convolutional neural network, on a related large chest X-Ray dataset that is tuned to classify between four classes such as normal, pneumonia, another disease, and COVID-19. The authors have used three well-known CNN models with an increasing number of layers such as AlexNet with 8 layers, VGGNet with 16 layers, and ResNet with 50 layers was used. VGGNet was the best performing network out of the three models [10]. The authors have used an efficient Net family of deep learning architecture. The authors have used a training dataset that comprises CT scan images of COVID patients (253) and Normal patients (291). The limitation of this work is that the training dataset used was not enough for the detection of COVID-19. Also, the model has an overall accuracy of only 90% which is much lower due to less data availability of training and testing datasets [11].

3. Design Methodology

3.1 VGG 19

VGG is a successor to AlexNet. It is discovered by the Visual Geometry Group at Oxford hence the model is given the name

VGG. To enhance the delicacy of the algorithm it uses deep neural networks in addition to the normal structure. VGG algorithm structure depicts that it has a 7×7 receptive field as per the result of 3×3 convolution with stride 1. It shows that it has very small parameters to train. VGG-19 has 19 weight layers among them 3 layers are fully connected. It also has five pooling layers (3,13). VGG Algorithm is given as an input of size 224×224 RGB image. It takes the image input pixel by pixel of values range of 0-255 and finds the differences of average values among the 19 layers. Architecture of the VGG-19 is shown in Fig. 1.

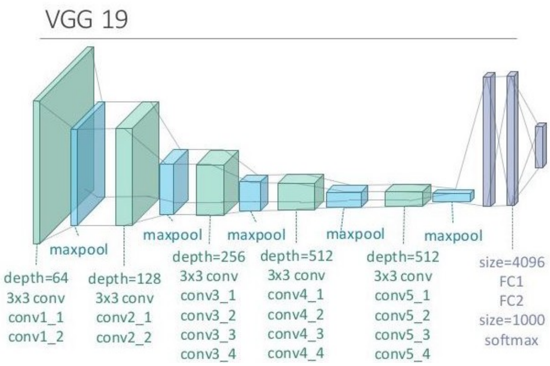


Fig. 1. Architecture of VGG 19.

3.1.1 Structure of VGG

Input: 224×224 pixels of the images are considered to be the input to the system. The generator model in the ImageNet database has 224×224 pixels of image centers to maintain consistency in the datasets.

Convolution Layer: VGG layers work with a minimum 3×3 field. In the VGG-19 algorithm, the input image is sent to the 1×1 convolution filter that produces the transformation to the input. An unconventional approach such as AlexNet and ReLu (Remedied direct unit activation function) unit produces less training time. Here, The ReLu unit produces the output as the same if the value results in positive otherwise it yields negative. The convolution stride (i.e., the number of pixel shifts over the matrix input) is made fixed on one pixel to maintain the spatial resolution once convolution is applied to it.

ReLu: ReLu is a rectifying linear unit. A unit that's made to rectify and compensate for signal parsing errors similar to when we're forced to encapsulate epsilon (infinitely small) and we've to work around that. So ReLu " Steers back the signal " to where it's supposed to be headed so that the signal doesn't explode or vanish. There of ReLu act kind of like " Safety stops " on the sides of the roads so you don't steer off the road when you're driving.

Max Pooling: Pooling together the maximum sample you can find in an average area of taking strides. Strides are the average functional kernel mapping in a square illustration plot that averages out the value samplings of some space. So you may have an 8×8 total square with four 4×4 squares. So, you can reduce that to a maximum of every 4×4 square. By, putting them together and getting a 4×4 Forecourt to replace the earlier 8×8. It effectively takes "the biggest impact features" and thereof, "the largest information to retrieve" (read coarsest features) and then ignores the minor features. so it outcome is left with a lower sample space (lower) but you keep the coarsest features, you keep the largest representative of the information. It is a trade-off for sake.

Hidden Layer: Hidden Layers in the VGG-19 model use ReLu as an activation function. The hidden layers inside the VGG-19 algorithm are used to achieve better results and also increase the training time. But, it will not affect the LRN (Local Response Normalization). As we see the outcome, there is no enhancement in the outcome using hidden layers.

Fully Connected Layers: VGG 19 has three fully connected layers. From that three layers, 4096 channels are available in the first two layers. But, the third layer has 1000 channels for every class. There are two major drawbacks to VGG-19.

1. It is slow because training time is high.
2. Considering Bandwidth and disk space, the architecture of VGG 19 is large.

3.2 ResNet 50

ResNet 50 has a 7×7 kernel size of Convolution Layers and 64 different bits within a stride in a single layer. It uses a Max pooling layer with a stride size of 2. Added to it another convolution layer encloses 1×164 followed by 3×364 kernel size with the 1×256 kernel at the end. The above three kernel sizes are repeated and processed thrice and yield nine layers finally. 12 Layers of Convolution layers formed with the kernel size of 1×1, 128, 3×3, 128 followed by 1×1, 512 kernel sizes processed repeatedly four times. It also has a Kernel size of 1×1, 256 and two times of 3×3, 253 and 1×1, 1024 of the repeated process of six times to produce 18 layers. Finally, one more 1×1,512 kernel with two more of 3×3, 512 and 1×1,2048 repeatedly works three times adding up to 9 such layers. At the end of the architecture, here is an average pooling layer that is completely associated with 1000 hubs with a softmax function to give a single layer. The Architecture of the ResNet 50 is shown in Fig. 2.

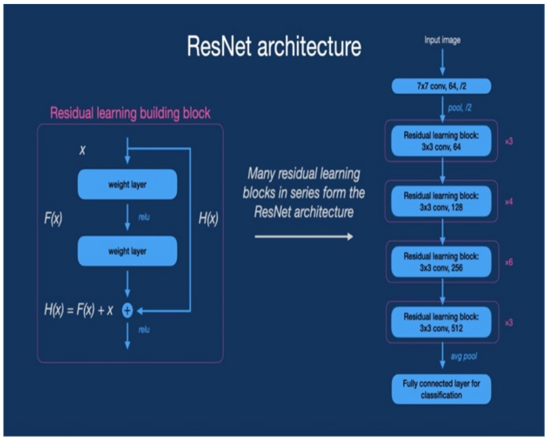


Fig. 2. Architectural diagram of ResNet 50.

3.3 Inception V3

Inception V3 is a deep learning- based Convolution Neural Network. The proposed work applies the Inception V3 model to the COVID19 X-ray images and CT Scan images for detecting COVID19. A superior version of the Inception Model results in High accuracy with low power computational effects. Architecturally Inception V3 Model has 42 layers to provide optimized results. The Architecture of the Inception V3 is shown in Fig. 3.

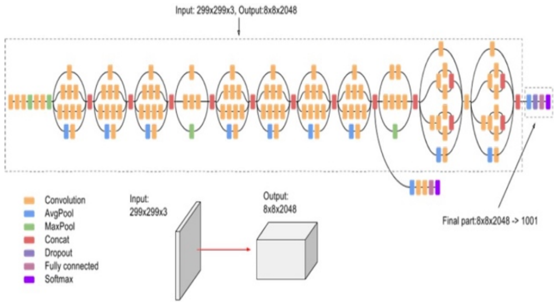


Fig. 3. Architectural diagram of Inception V3.

The added advantage involves different steps.

1. Factorized Convolutions in Inception V3 reduce the computational efficiency by reducing the number of parameters.
2. Faster training of CNN outcomes by replacing the bigger convolutions with smaller convolutions. Consider, 25 parameters are available in the 5×5 channel. on top of it, two 3×3 channels are added and give 18 (3×3 + 3×3) parameters.
3. 1×3 convolution along 3×1 convolution yields a 3x3 convolution. After the yield of 3×3 convolution, if we degrade the convolution of 3×3 to 2×2 then the parameters in the model will be large and it produces deviated results in the proposed methods where it shows the asymmetricity characteristics.
4. While Initializing Inception V3, there is a regularizer in the model which is also called an auxiliary classifier that degrades the misfortune that happened within the network by including the losses caused to the main network of CNN in between the multiple layers.
5. Pooling operations handle the Grid size reductions to maintain higher efficiency.

3.4 Xception

The Extreme version of Inception is known as Xception. Modification in the depth-wise separation gives more precise results than Inception V3 for Image Classification. The Architecture of the Xception is shown in Fig. 4.

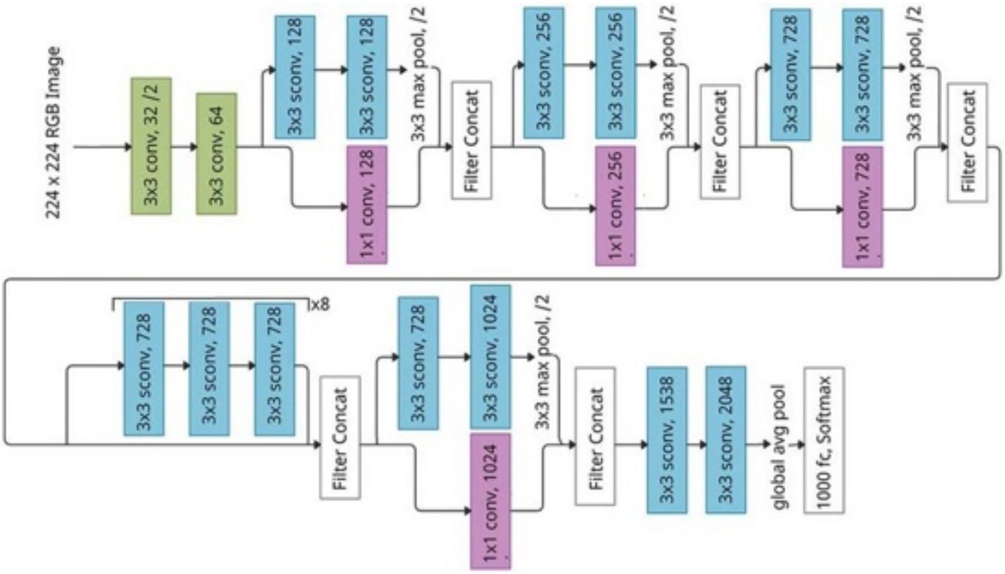


Fig. 4. Architectural diagram of Xception.

The Xception algorithm of DCNN was applied on COVID 19 X-ray datasets to accurately and precisely detect the COVID affected patients. The architecture of the Inception model consists of a 1×1 convolution layer to compress the original input to the necessary input spaces and it is applied with the filters indepth to compress the input space into 1×1 convolution layers. It is the complementary to Inception V3 model which is a depthwise seperable convolution. The presence of ReLu Non-linearity in the Inception model and the absence of nonlinearity in the Xception model makes the difference between them.

4. Implementation

4.1 Proposed System-COVID 19 detection

The proposed model shown in Fig. 5 builds a powerful model for detecting accurate COVID-19 disease using X-ray images. For the identification of COVID-19 disease, the DCNN (Deep Learning-based Convolutional Neural Network) proves to be a very efficient architecture for image and video datasets thus, provide a very good accuracy. Also, In past activities, CNN has been proven to be the best choice for working with images and videos. In the COVID-19 proposed model, X-ray images have been tested and trained using pre-trained algorithms such as VGG-19, Resnet-50, Inception V3, and Xception architecture. Also, the working of each model is trained and tested by giving COVID positive and normal images on the existing data set obtained from GitHub and seeing the outcome. X-ray images are the input given to the different architectures listed above. Among them, VGG provides a training accuracy of 95.37% and validation accuracy of 95.76%, ResNet 50 provides a training accuracy of 83.81% and validation accuracy of 88.26%, Inception V3 provides a training accuracy of 95.16% and a validation accuracy of 93.06%, and Xception provides a training accuracy of 96.38% and validation accuracy of 95.02%.

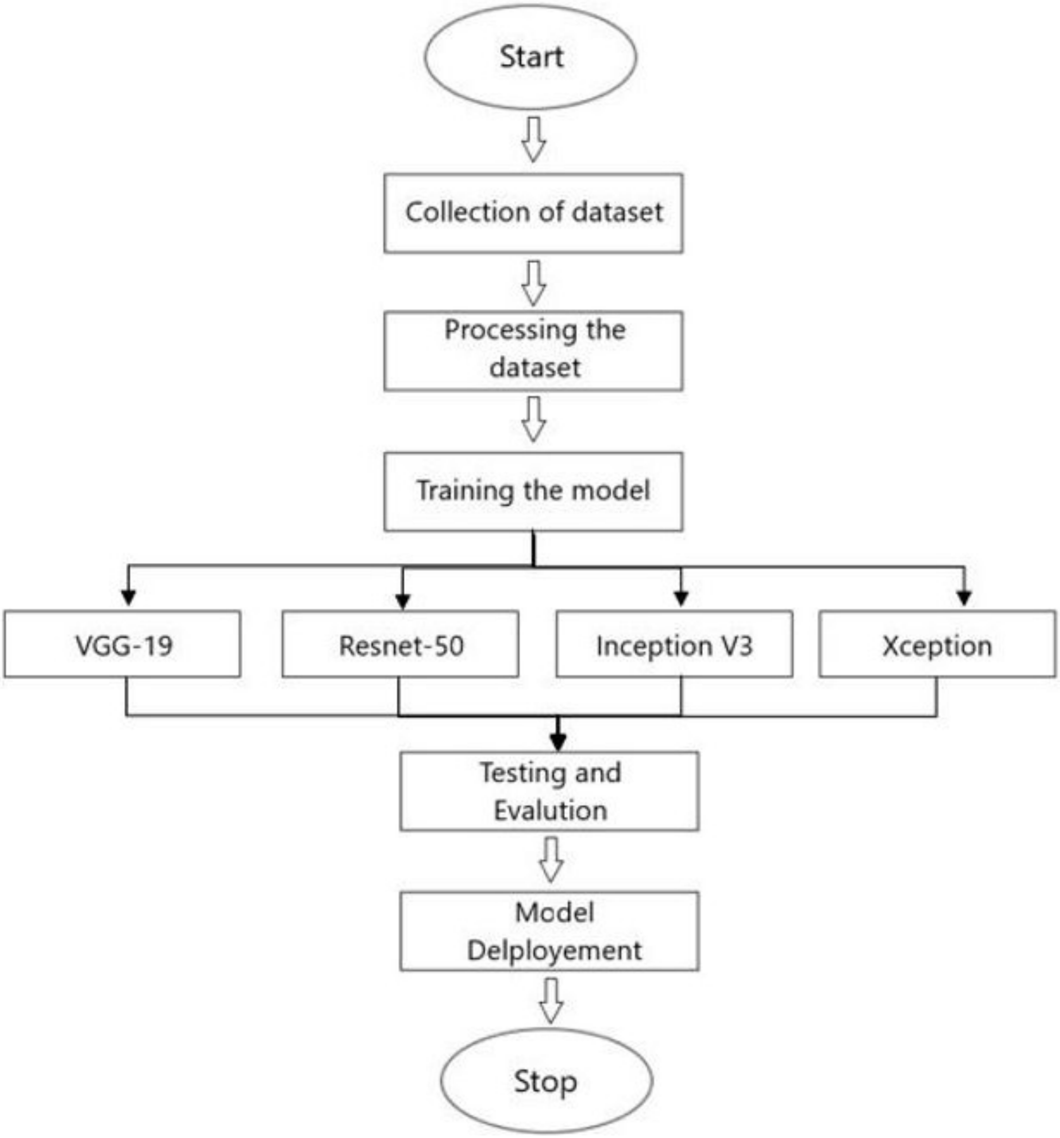


Fig. 5. Flowchart of Proposed System.

4.2 Splitting a Data set

The data set for training, testing, and validation has been downloaded from Kaggle, and the input images have been downloaded from GitHub Repositories for prediction. The below table represents the amount of images used for training, testing, and validation of the X-ray models. The sample data sets taken for the proposed methods is depicted in the Figs.6-7.

X-Rays Data Sets	Training	Testing	Validation
Covid	1855	350	50
Non Covid	2604	427	50

Fig. 6. X-Ray Dataset Images from Kaggle.

X- Ray Dataset	Training	Testing	Validation
Covid	1432	358	100
Non Covid	1040	261	100

Fig. 7. X-Ray Dataset Images from Github Repository.

5. Experiment Results

5.1 VGG 19

The trained model predicts the output in the form of an array consisting of 2 elements. When the value of the 0th index is higher than, it indicates COVID positive for (e.g., -[1,0]) ,and if the value of the 1st index is higher than, it indicates COVID negative e.g. -[0,1].This Figs. 8-9 below depicts the Confusion matrix of VGG-19 for the X-Ray images with and without normalization by class support size (number of elements in each classes)

This kind of normalization is useful for cases of class imbalance and also gives more visual interpretation of which class is being misclassifies. From the Figs. 8-9 we can make out True positive COVID cases 95% and 99.6% True non- COVID cases from the testing set. It is Falsely classifying 4.5% COVID cases and 1.5% non-COVID cases.

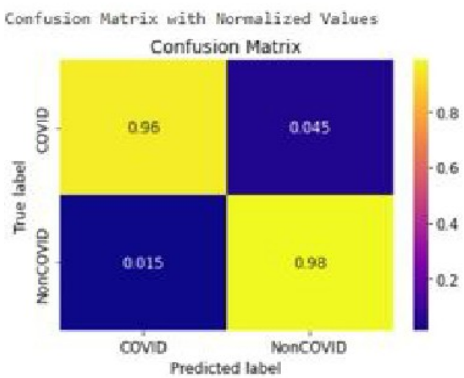


Fig. 8. VGG-19 Confusion matrix with normalization for X-ray model.

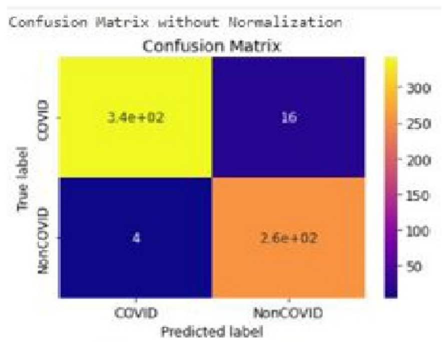


Fig. 9. VGG-19 Confusion matrix without normalization for X-ray model.

Figs. 10-11 show the Accuracy and loss model of VGG-19. Visualizing the training loss versus validation loss or training accuracy versus validation accuracy over a number of 250 epochs is important so that model is not undertrained and not overtrained. From the Figs. 10-11, it is identified the accuracy and loss graph of training and validation is not exactly same. Figs. 12-13 show the X-ray model using VGG-19.

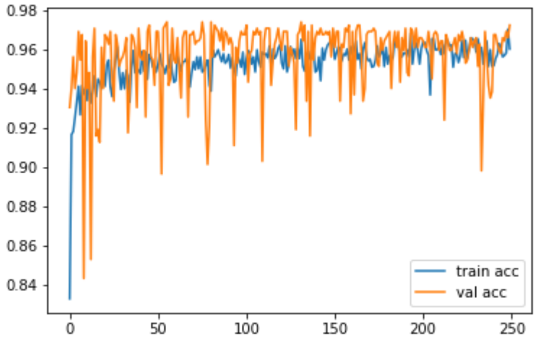


Fig. 10. VGG-19 Accuracy of X-Ray model.

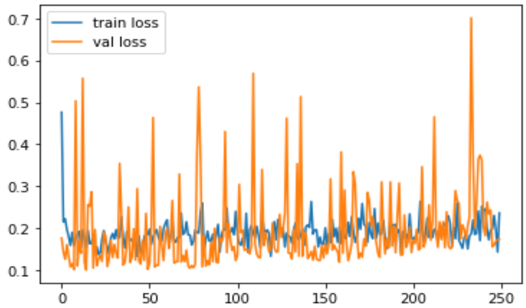


Fig. 11. VGG-19 Loss of X-Ray model.

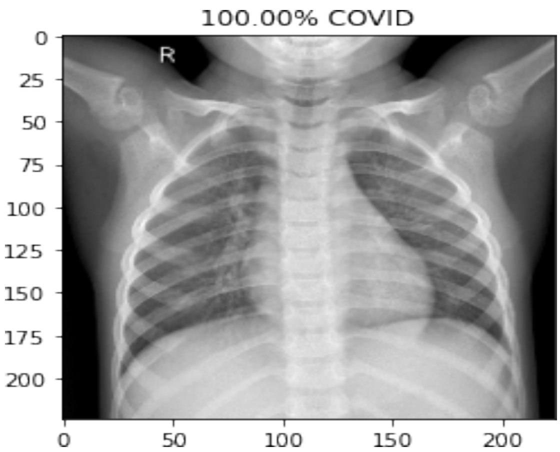


Fig. 12. X-Ray Model (For patient affected with COVID) using VGG-19.

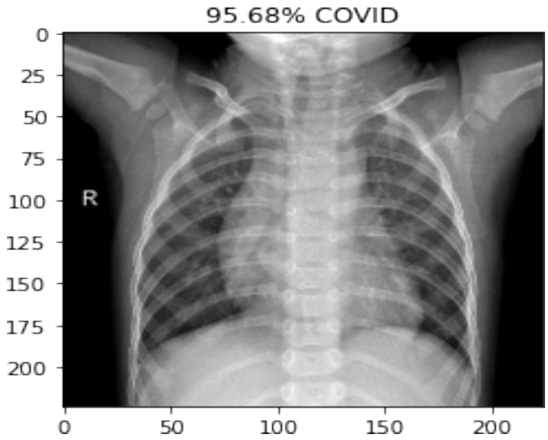


Fig. 13. X-Ray Model(For patient affected with COVID) using VGG-19.

5.2 ResNet 50

The trained model predicts the output in the form of an array consistingof 2 elements. When the value of the 0th index is higher than, it indicates COVID positive for (e.g., -[1,0]) , and if the value of the 1st index is higher than, it indicates COVID negative e.g. -[0,1].

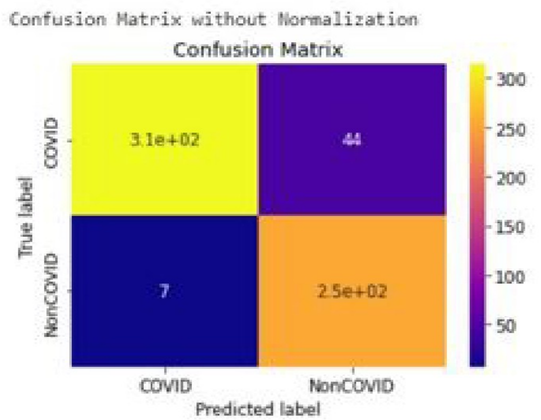


Fig. 14. ResNet 50 Confusion matrix with normalization for X-ray model.

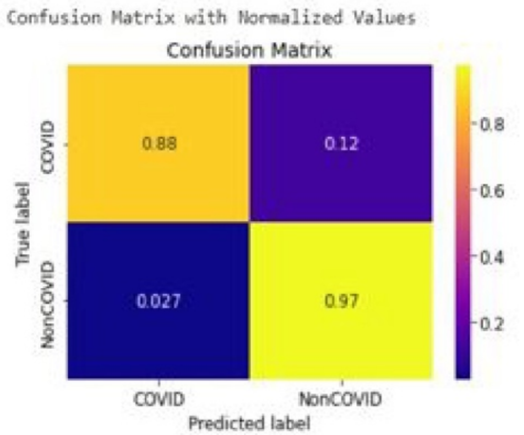


Fig. 15. ResNet 50 Confusion matrix without normalization for X-ray model.

These Figs. 14-15 above depict the Confusion matrix of ResNet 50 for the X-Ray images. we can make out True positive COVID cases 88% and 97%True non-COVID cases from the testing set. It is Falsely classifying 12% COVID cases and 2.7% non-COVID cases.

Figs. 16-17 show the Accuracy and loss model of ResNet 50, From the Figs. 10-11, it is identified the accuracy and loss graph of training and validation is not exactly same. Compared with VGG-19 it is less accurate and producing more loss.

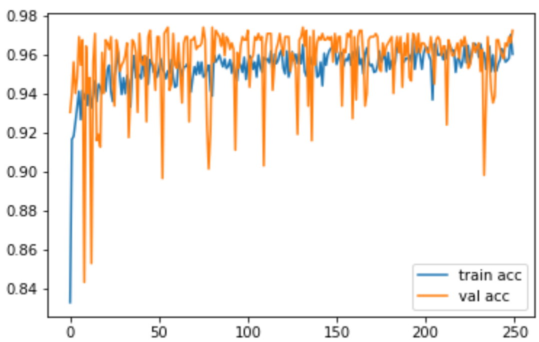


Fig. 16. ResNet 50 Accuracy of X-Ray model.

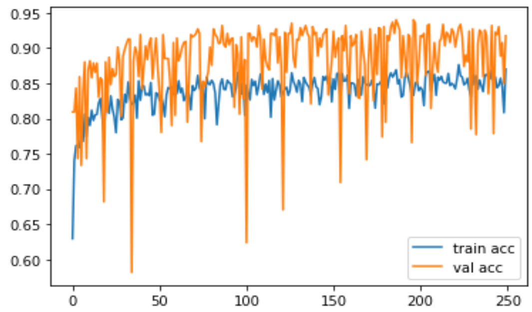


Fig. 17. ResNet 50 Loss of X-Ray model.

Figs. 18-19 show the detection of COVID and Non COVID patients of X-ray Images using ResNet 50 Algorithm.

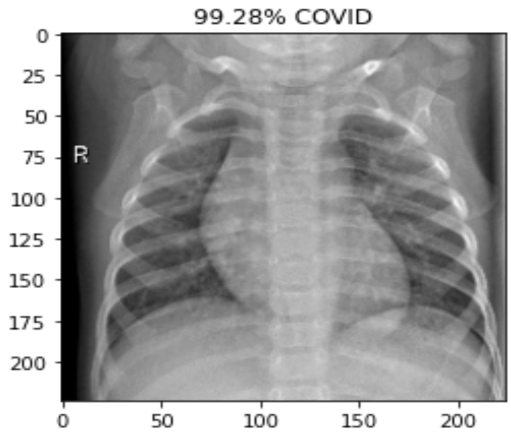


Fig. 18. X-Ray Model (For patient affected with COVID) using ResNet50.

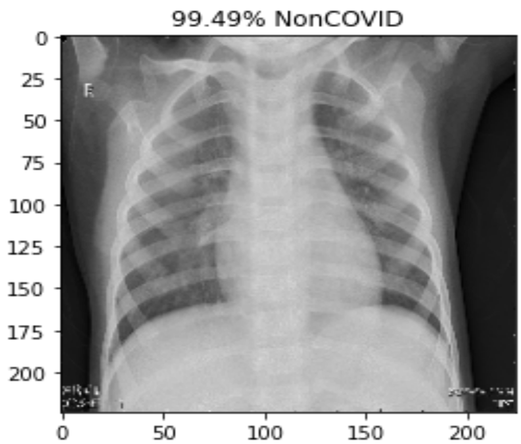


Fig. 19. X-Ray Model (For patient affected with COVID) using ResNet 50.

5.3 Inception V3

The trained model predicts the output in the form of an array consisting of 2 elements. When the value of the 0th index is higher then, it indicates COVID positive for e.g. -[1,0], and if the value of the 1st index is higher then, it indicates COVID negative e.g. -[0,1]. This Figs. 20-21 above depicts theConfusion matrix of Inception V3 for the X-Ray images. we can make out True positive COVID cases 96% and 93%True non- COVID cases from the testing set. It is Falsely classifying 3.9% COVID cases and 6.9% non-COVID cases. Figs. 22-23 shows the Ac- curacy and loss model of Inception V3. it is identified the accuracy and loss graph of training and validation are almost closed to each other. Compared with VGG-19 and ResNet 50 this model is more accurate and producing less loss. Figs. 24-25 shows the detection of COVID and Non COVID patients of X-ray Images using Inception V3 Algorithm.

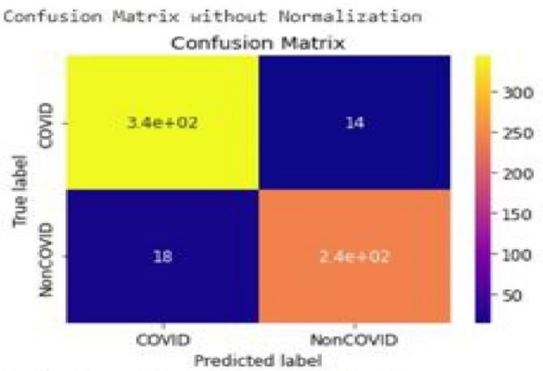


Fig. 20. Inception V3 Confusion matrix with normalization for X-ray model.

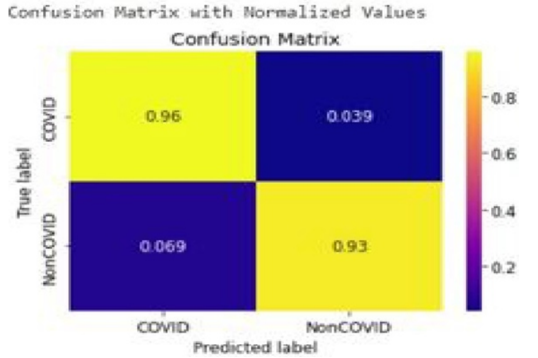


Fig. 21. Inception V3 Confusion matrix without normalization for X-ray model.

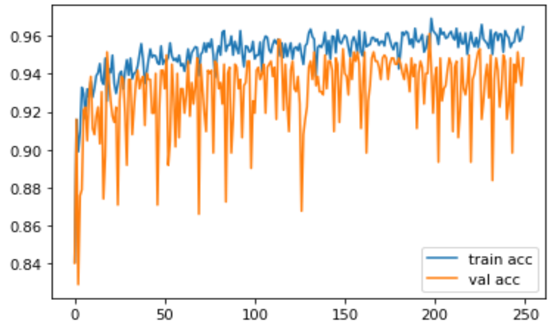


Fig. 22. Inception V3 Accuracy of X-Raymodel.

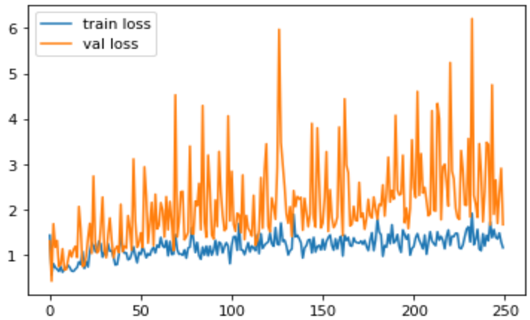


Fig. 23. Inception V3 Loss of X-Ray model.

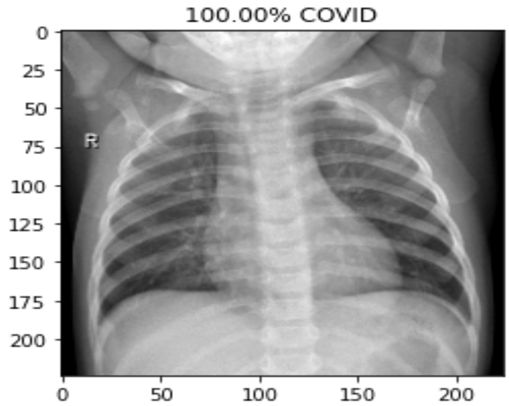


Fig. 24. X-Ray Model (For patient affected with COVID) using Inception V3.

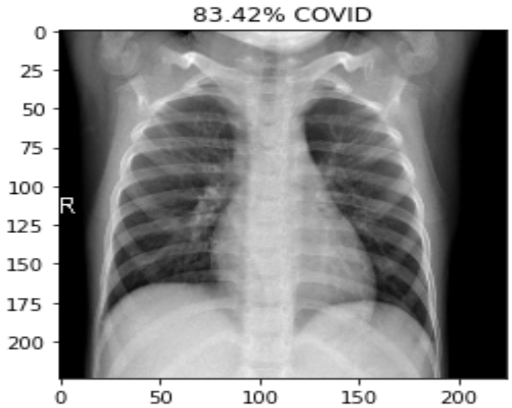


Fig. 25. X-Ray Model (For patient affected with COVID) using Inception V3.

5.4 Xception

Confusion matrix is used to evaluate the quality of the output of a classifier on X-ray datasets. The diagonal elements represents number of points for which predicted cases is equal to true cases, while off diagonal elements are those that are mis- classified cases. In the Xception Model, the trained model predicts the output in the form of an array consisting of 2 elements. When the value of 0th index is higher it indicates COVID positive for e.g. -[1,0] and if the value of 1st index is higher it indicates COVID negative e.g. - [0,1]. This Figs. 26-27 above depict the Confusion matrix of Xception model for the X-Ray images. we can make out True positive COVID cases 97% and 98%True non-COVID cases from the testing set. It is Falsely classifying 2.8% COVID cases and 2.3% non-COVID cases. Figs. 28-29 show the Accuracy and loss model of Xception.it is identified the accuracy and loss graph of training and validation are almost similar. Compared with VGG-19, ResNet 50 and Inception V3 this model is giving more promising results.

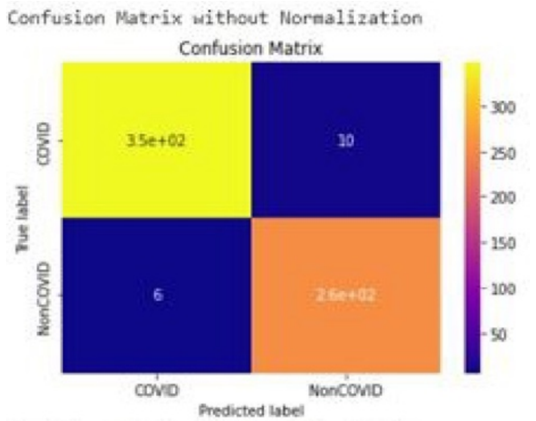


Fig. 26. Xception Confusion matrix with normalization for X-ray model.

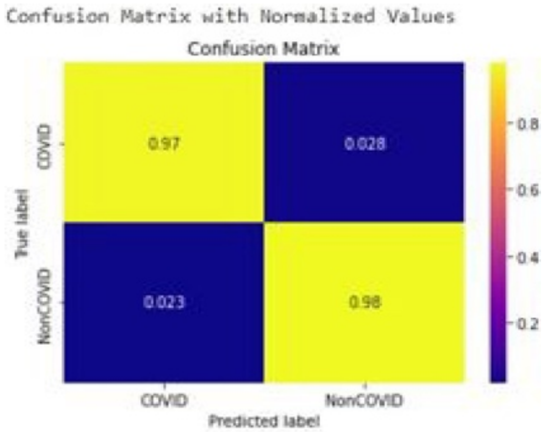


Fig. 27. Xception Confusion matrix without normalization for X-ray model.

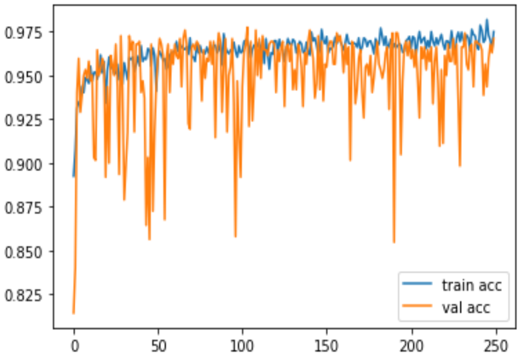


Fig. 28. Xception Accuracy of X-Ray model.

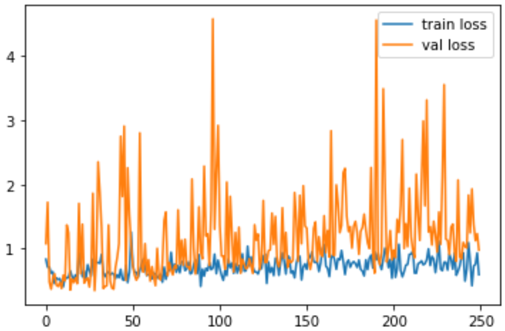


Fig. 29. Xception Loss of X-Ray model.

Figs. 30-31 show the detection of COVID and Non COVID patients of X-ray Images using Xception Algorithm.

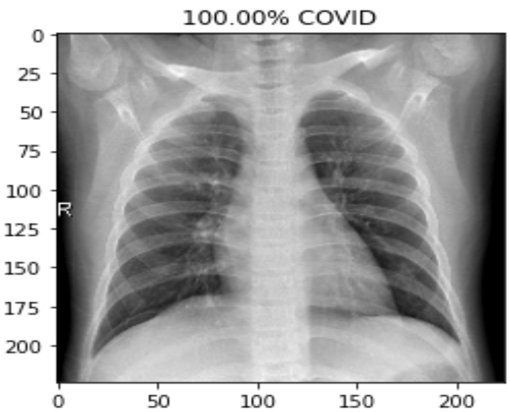


Fig. 30. X-Ray Model (For patient affected with COVID) using Xception.

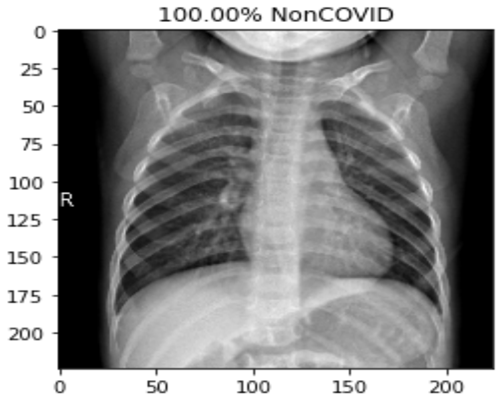
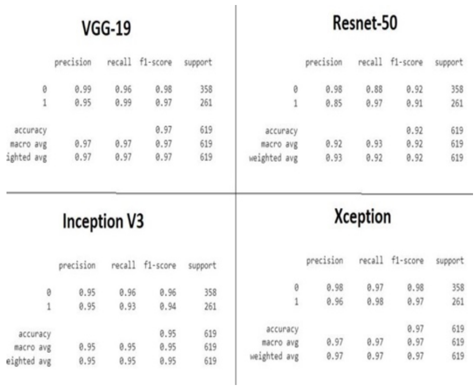


Fig. 31. X-Ray Model (For patient affected with COVID) using Xception.

From the below classification Report of X-Ray, we can evaluate the model's quality of predictions from a classification algorithm. It gives us a measure of True Positives, False Positives, True negatives, and False Negatives for predicting the metrics of a classification report. The different metrics obtained from the classification report are -Precision, Recall, and F1-score. Precision indicates the accuracy of positive prediction and recall provides the fraction of positives that were correctly identified. Whereas F1-score combines the two competing metrics precision and recall and sums them.



VGG-19

	precision	recall	f1-score	support
0	0.99	0.96	0.98	358
1	0.95	0.99	0.97	261
accuracy			0.97	619
macro avg	0.97	0.97	0.97	619
ighted avg	0.97	0.97	0.97	619

Resnet-50

	precision	recall	f1-score	support
0	0.98	0.88	0.92	358
1	0.85	0.97	0.91	261
accuracy			0.92	619
macro avg	0.92	0.93	0.92	619
weighted avg	0.93	0.92	0.92	619

Inception V3

	precision	recall	f1-score	support
0	0.95	0.96	0.96	358
1	0.95	0.93	0.94	261
accuracy			0.95	619
macro avg	0.95	0.95	0.95	619
eighted avg	0.95	0.95	0.95	619

Xception

	precision	recall	f1-score	support
0	0.98	0.97	0.98	358
1	0.96	0.98	0.97	261
accuracy			0.97	619
macro avg	0.97	0.97	0.97	619
weighted avg	0.97	0.97	0.97	619

Fig. 32. Comparison of Classification Report -X-Ray Model.

6. Conclusion

In the proposed model, the Deep neural network model is implemented and it works very well on images and video datasets. The CNN is a powerful algorithm as it can try to extract those features which are even not visible to human eyes and it provides a very good performance as well if the layers are decided properly. Four different architectures of CNN were trained and tested on X-Ray Images based on the transfer learning approach as they had significantly higher accuracies. Out of all four Architecture which we have tested on X-ray Images Xception model was the best performing model followed by VGG-19. ResNet-50 had the lowest accuracies of all the four architectures. This implies that going much deeper into networks doesn't mean that the performance of the model increases which can be seen in our case as VGG-19 outperforms the ResNet-50 model which is 19 layers deep as compared to ResNet-50 which is 50 layers deep. We had obtained an accuracy of up to 98% which indicated that COVID-19 detection using this method could be very efficient and it can be employed as an initial screening of patients because of its promising performance.

Future Scope

- Combining both X-Ray and CT Scan models into one single model for accurate detection.
- Using the existing model weights and retraining them using various lungrelated diseases for developing a lung disease classification model.
- To perform L1 and L2 Regularization for further improving the model.
- To perform hyper parameter tuning like changing learning rates, epsilon, early stopping, etc.,
- To classify the disease based on the severity of the infection on the input data.

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