Covid 19 Prediction System Using CNN

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Abstract. Today, the whole world is fighting the war against Coronavirus. The spread of the virus has been observed in almost all the parts of the world. Covid-19 also known as SARS-Cov-2 was initially observed in China which rapidly multiplied all over the world. The disease is said to spread by cough, normal cold, sneezing or when a person is in close contact with someone who is already infected. Therefore, the spread of the virus can occur when there is direct contact with an infected person or with the objects touched by the infected person. Hence, it is important to detect the contiguous spread of the virus and control it by taking appropriate measures. Several deep learning models have been used in detecting many diseases like Malaria disease, Lung infection, Parkinson's disease etc. Likewise, CNN model along with other transfer techniques is best proven to detect whether a person is infected with covid positive or not. The dataset consists of 1000 images of covid positive and normal x-rays. The proposed model has been trained and tested on the image dataset with the help of transfer learning models in order to improve the performance of the model. The models VGG-16, ResNet-50, Inception v3 and Xception have achieved an overall accuracy of 93%,82%,96% and 92% respectively. The performance of all the 4 architectures are analyzed, understood and hence presented in this paper. It is hence important to classify and detect covid positive infection and contribute towards making the world Covid-free.

Keywords: Covid-19, InceptionV3, Xception, Resnet, VGG16, CNN

INTRODUCTION

The novel COVID-19 or corona virus can be so severe that it has caused death in many cases. On March 11th, it was declared as a pandemic by the World Health Organization. The most affected countries are USA, India, China and rest of the world. In India, the first case was confirmed in the month of January,2020. They cause symptoms very similar to flu, fever, dry cough, head ache, short of breath, loss of taste and weakness. The virus invades the body and competes with the healthy cells. It latches its spiky surface proteins to receptor on healthy cells, especially those in the lungs. The most widely accepted method to detect COVID- 19 is the RT-PCR test, CT-scan, Antibody test. While all the above stated methods are usually a time taking process which gives out the results usually 1 day after the test. Hence, detection of the virus using chest X-rays in a shortest time interval proved to be more precise, accurate and effective. X-rays have an added advantage of cost effectiveness over CT -Scans, and have hence been used using Convolutional Neural Networks and Transfer learning. CNN or ConvNet[1][2] is a deep learning algorithm mainly used for image classification and recognition because of its high accuracy. The TensorFlow based classification is more successful and easier. The success comes from its potential to recognize and pin down the hidden parameters or attributes in the hidden layer. The CNN[3][4] follows a hierarchical model which works on building a network and processes the output. The dataset consists of 1000 chest Xray images which are normal and covid Infected. The images are preprocessed and the CNN model is trained on set of X-rays and are later tested to determine the severity of the infection in the patient and take appropriate precautions and help to battle the war against the virus. In this paper, we have proposed and evaluated 4 models for COVID-19 detection using Convolutional Neural Networks and transfer learning based -VGG16, Inception, Xception and ResNet-50[5] architectures using chest X-rays. Comparison and evaluation of each of these transfer learning techniques for faster result and better efficiency is the potency of this paper.

The next sections of the paper throws light on some of the related works and background. This is then followed by proposed methodology which are then evaluated. The results are predicted by classifying the chest x-ray into Covid or non-Covid. The conclusion is drawn in Section VI and the references are given in the end of this paper.

Hardware and Software requirements-The project is set-up on jupyter notebook using Anaconda navigator using python. Modules and packages like tensorflow and keras act as a powerful tool. The hardware requirements are 16GB or 8GB RAM, Quad core Intel Core processor, SSD with at least 256 GB of storage, CPU i5 9th or 10th Gen.

BACKGROUND AND RELATED WORK

Research has been carried out for the classification of COVID infection either by chest X-rays or CT - Scans. Researches have proposed various deep learning models like VGG16 and VGG19 which gave an accuracy of 93% and 97% respectively. But, these model take into account only few image datasets for their classification and thus, producing good amount of accuracy. Another research group detected COVID 19 using CNN, much similar to cheXNet algorithm, that was published by Stanford University, to achieve the results. The dataset was collected from the Kaggle website, with 500 chest Xray images giving an accuracy around 89.7%. Another research group focused on CNN and Inception V3, published by Nazmus Shakib, Silvia Sanjana, Nusrat Jahan, whose accuracy results turned out to be 84.92% for CNN architecture and 85.94% on Inception V3 architecture. Hence, our main motive is to evaluate the performance of 4 models-VGG16, Inception-V3, ResNet50, Xception and discover the best model evaluated for our dataset which reduces the computation time and gives the best accurate results.

PROPOSED METHODOLOGY

Dataset Modelling

The dataset is taken from Kaggle COVID -19 radiography database. The dataset has around 550 images of infected X-rays and 450 images of normal X-rays. All the images are in portable .png or .jpg format. The models take the images into pixel values and are further normalized in the interval [0,1]. The entire dataset consisting of image X-rays is primarily split in the ratio of 80:20 as training data and validation data and are visualized. The dataset is developed and updated by a group of experts from Qatar University. The directory consists of 2 folders, one of Covid 19 samples and the other folder has normal samples. The main objective is to make use of this database and do a scholarly and effective research.

Building the CNN model

The classification of images into Covid or Non-Covid is done by Convolutional Neural Networks [Fig 1] and 4 transfer learning models, namely VGG16[6][7], Inception-V3[8][9], Xception[10][11] and ResNet50[12].

In this paper, we have first used CNN algorithm which follows a hierarchical model which automatically learns through backpropagation to classify the medical X-ray images. The input image is fed to the model for training the set of images. The input shape of the image is specified as [64,64]. The model has 4 convolutional layers. For the first convolutional layer we have specified the filter to be of size 32, the kernel size being [3,3] with relu activation function. The filter size is increased to 64 and 128 in the next consecutive layers. The convolutional layers are zero padded so as to not disturb the input resolution. The max pool layer selects the maximum elements that have the most distinguished and notable features or attributes. The benefit of max pool layer over average pool layer is to extract the bright features of the X-rays image[13][14] for feature selection and extraction. The first layers basically extracts the most basic patterns like shapes, edges which is then extended to complex and more complex attributes in the top layers. To prevent the CNN model from overfitting, we set the dropout to be 0.25 so as to increase the accuracy. Finally we flatten the layer and pass it to the fully connected layer. The first dense layer uses relu activation function and the second dense layer uses sigmoid activation function.

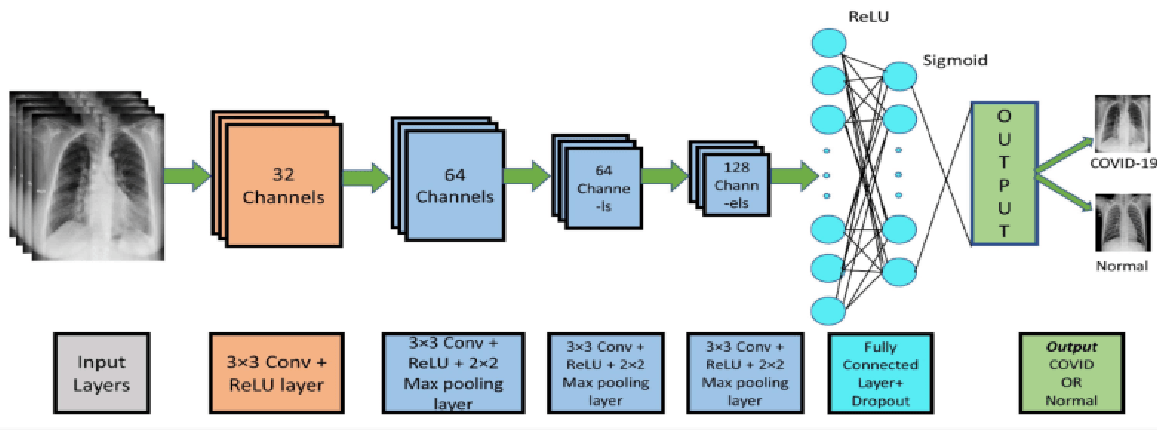

FIGURE 1. Block diagram architecture using CNN model for the classification of chest X-rays.

The parameters or weights are the learnable parameters which are used for convolutional layers.The first convolutional layers is very basic and has only 896 parameters. The pool layers do not have any parameters, hence they are zero and the fully connected layers is expected to have the highest number of parameters. The total parameters for CNN models is 7,503,170 with non-trainable parameters and 7,503,170 trainable parameters. We then compile the model using binary cross entropy and optimizer being adam optimizer. The model is trained for 30 epochs and the results are evaluated in Section *IV*.

Along with CNN algorithm, we have also proposed 4 deep CNN models [Fig 2] where we take a pre-trained model and retrain it to perform another task. The labels of one task is used to train the model which is then adapted and reused on another model. This in turn, saves the amount of time required to train the models. Hence, the pretrained model improves the computational power and delivers the results superfast.

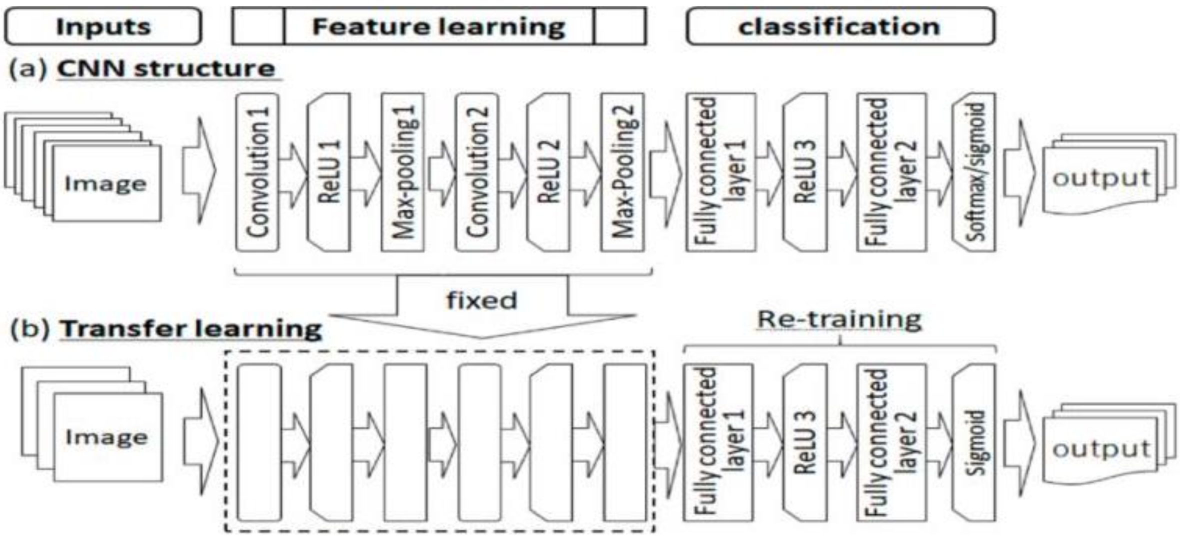

FIGURE 2. Coupling of CNN with Transfer learning models

Transfer Learning Models

VGG16*:* VGG16[Fig 3] or Visual Geometry Group is a simple, flexible and organized deep CNN architecture proposed by K. Simonyan and A. Zisserman.It was used on ImageNet dataset with an accuracy of 92.7 %. The 16 layer architecture has 13 convolutinal layes,2 max pool layers and 1 softmax activation function[15][16].

The input specification of the image is taken as [224,224]. Thus, the images need to be resized before they are fed into the pre training network.

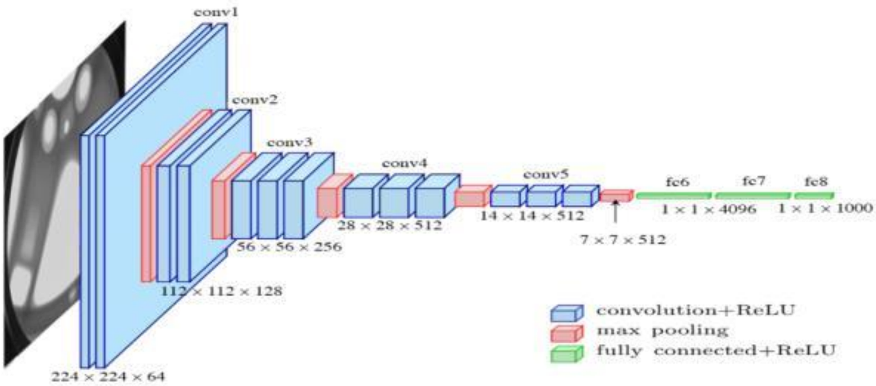

FIGURE 3. Proposed model using VGG-16 architecture for classification into Covid and Non-Covid.

The resized image is of the size [224,224], is the default size of the image for VGG-16 model. The convolutional layer has a filter size of 3*3 and stride =1 and always used the same padding. The max pool layer of filter 2*2 of stride 2. Initially, the number of filters is taken as 64, which then goes on doubling for the next consecutive layers. We have used SGD as the optimizer with categorical loss entropy as the loss function. The 16 layers form a large network and used soft-max activation function in the dense layer for its classification. The parameters or weights are the learnable parameters which are used for convolutional layers. The first convolutional layers is very basic and has only 208 parameters. The pool layers do not have any parameters ,hence they are zero and the fully connected layers is expected to have the highest number of parameters. The total parameters for VGG-16 models is 25,100,046 with non-trainable parameters.

Resnet50*:* ResNet50[Fig 4] or deep Residual Network is another transfer learning model which is about 50 layers deep. It was also a winner of the ImageNet challenge in 2015 and focused on the issue of vanishing gradient. The skip connection is the added bonus for this architecture. The gradients can traverse in the reverse direction from the last layers to initial layer. Resnet50 model introduces the concept of skip connection. It basically consists of 48 convolutional layers, 1 MaxPool layer and one Average Pool layer. The parameters or weights are the learnable parameters which are used for convolutional layers. The input layer has 0 parameters.The first convolutional layers is very basic and has only 9474 parameters. The pool layers do not have any parameters ,hence they are zero and the fully connected layers is expected to have the highest number of parameters. The total parameters for ResNet models is 32,009,730 with 53,120 non-trainable parameters and 31,956,610 trainable parameters.

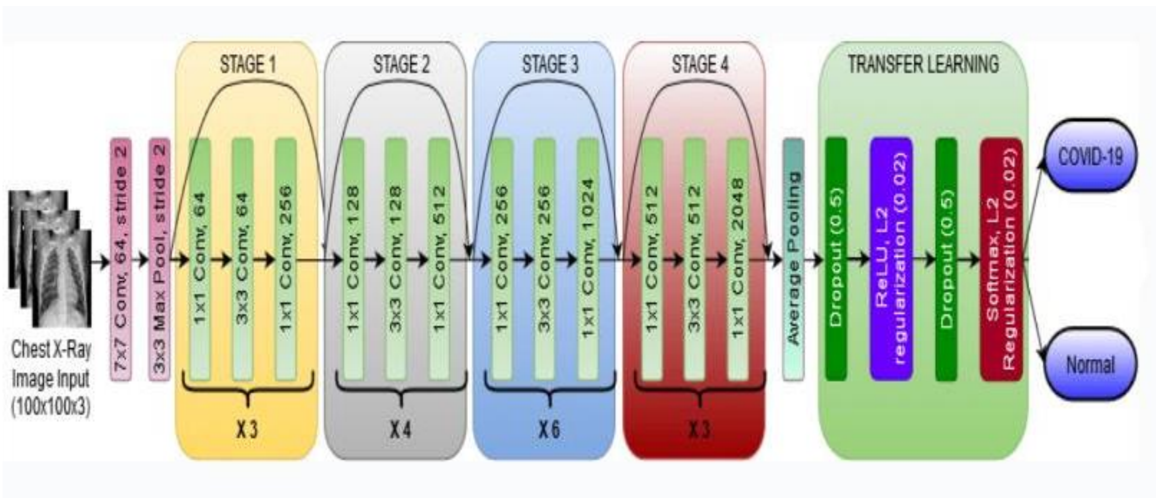

FIGURE 4. Proposed model using Resnet-50 architecture for classification into Covid and Non-Covid.

The input specification of the image is taken as [224,224]. Thus, the images need to be resized before they are fed into the pre training network. The resized image is of the size [224,224]. Initially, it consists of a convolutional and a Max Pool layer. It then passes through 4 stages where each stage is multiplied 3 times, 4 times, 6 times and

3 times respectively. The semi-circular arrow represents an identity block and the arrow formed by the transition of one stage to another forms a convolutional block. In other words, the convolutional layer is added in the shortcut path when the input size and the output size do not match.

***InceptionV3**:* Inception V3[Fig 5] is another CNN architecture which is best suitable for classification of X-ray images. has factorized convolutions that reduce computational efficiency due to reduced parameter with the benefit of smaller convolutions.

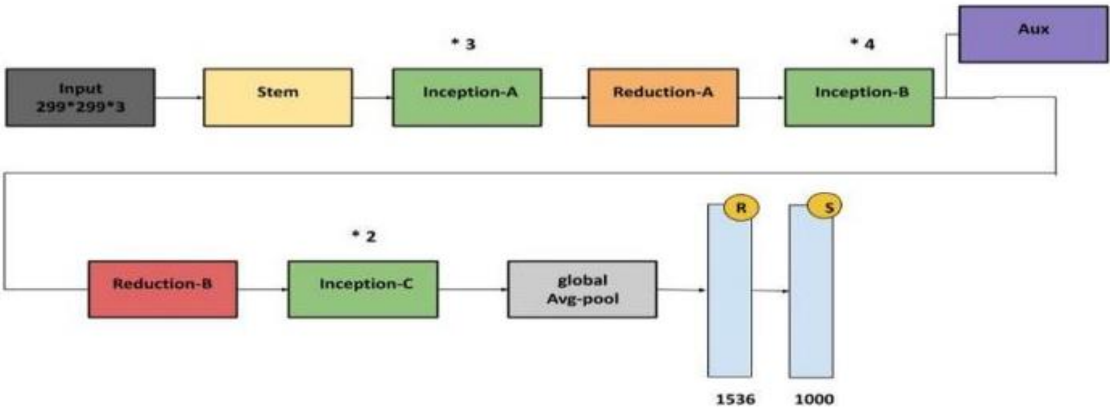

FIGURE 5. Proposed model using Inception-V3 architecture for classification into Covid and Non-Covid

The Inception V3 model proved to be more efficient than Inception V2 and Inception V3 without any trade-off in its speed. The model is said to achieve its optimization by factorizing into smaller convolutions and spatial factorization into asymmetric convolutions.

The input specification of the image is taken as [299,299]. Thus, the images need to be resized before they are fed into the pre training network. The resized image is of the size [224,224]. The benefit of Auxiliary classifier is mainly used to tackle the problem of vanishing gradient and has proven to show higher accuracy. This is done with the help of classifier heads whose prime focus is to improve the training speed of the convergence model. The gradient is pushed to initial layers and hence, tackle the issue of vanishing gradient. The reduction block in the architecture, is to reduce the grid size by expanding the network filter using parallel blocks of convolution and Max Pool layers which are later concatenated. The 2 dense layers in the end act as classifiers which are the Auxiliary classifiers with relu activation function and softmax activation function which performs the prediction.

The parameters or weights are the learnable parameters which are used for convolutional layers. The input layer has 0 parameters. The first convolutional layers is very basic and has only 864 parameters. The pool layers do not have any parameters , hence they are zero and the fully connected layers is expected to have the highest number of parameters. The total parameters for Inception V3 models is 21,062,186 with 20,861,480 non-trainable parameters and 200,706 trainable parameters.

***Xception**:* Xception [Fig 6] is another model that goes upto 71 layers deep. The input image size is specified to be [299,299].We can hence use the Xception model for the classification of the image. It involves depth wise separable convolutions. The images in the dataset are of different dimensions. Thus, the images need to be resized before they are fed into the pre training network. The parameters or weights are the learnable parameters which are used for convolutional layers. The input layer has 0 parameters. The first convolutional layers is very basic and has only 864 parameters which is then extended for complex features. The pool layers do not have any parameters, hence they are zero and the fully connected layers is expected to have the highest number of parameters. The total parameters for Xception models is 32,009,730 with 53,120 non-trainable parameters and 31,956,610 trainable parameters.

The model is separated as Entry flow, Middle flow and Exit flow. The data traverses from entry flow through middle flow and then to the exit flow. The middle flow is repeated 8 times. The model used soft-max activation function at the output layer. The architecture has also made used of skip connections in order to merge the 2 layers in order to overcome the problem of vanishing gradient.

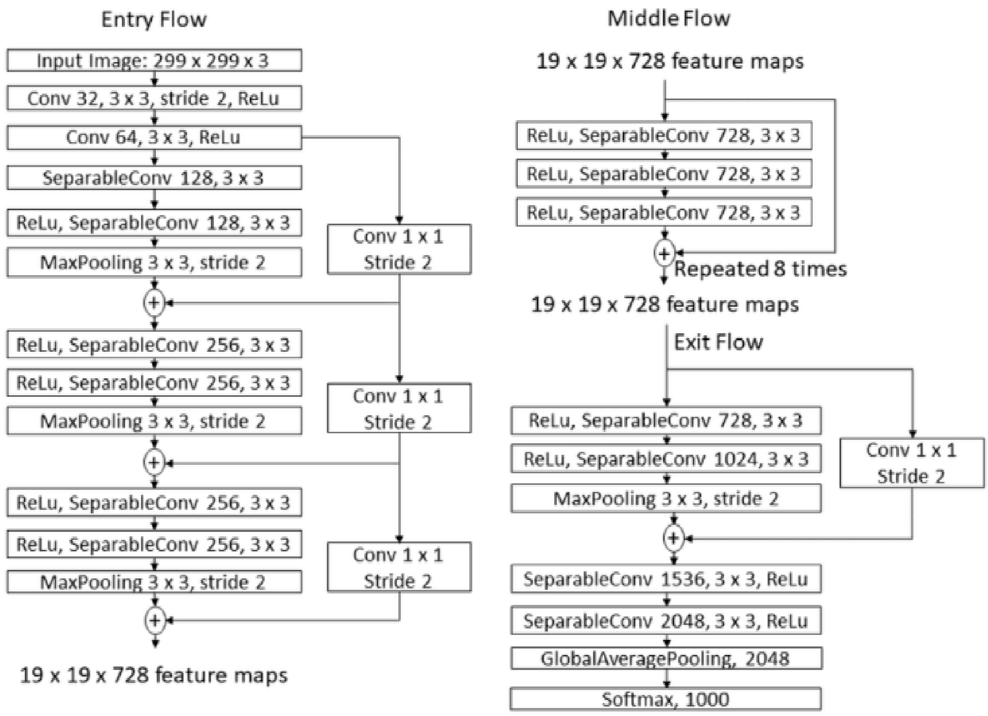

FIGURE 6. Proposed model using Xception architecture for classification into Covid and Non-Covid.

For all the four architectures, we pass the input image to each of these models. We define the input specification that has to be fed to the model. Each of the convolutional models along with the filter and kernel size is specified which is then passed for Pooling. The classification of Pooling can be of 2 types Max Pooling and Average Pooling. In all our architectures we have made use of Max Pooling as Max pooling helps in the better selection of the features by extracting the bright regions of the X-ray. Hence it is done by selecting the maximum value in the pooling layer while in case of average pooling the background region may predominate the region of interest. The maximum pooling is calculated by the formula fmax(x)=max{xi}Ni=1. Hence Max pooling is the best choice for the evaluation of the models. They are then flattened the parameters into a 1-Dimensional array and passed through the fully connected layers wherein based on the weight the dense layers classifies the output. We finally compile the model using the best optimizers for each of these architectures and compute the loss function and propose the model to do the binary classification into Covid or Normal.

Training the model

The images are trained at different angles, horizontal-flips, rotations or shifts with a data augmentation technique called Image Data Generator. Next, training of the model was performed, with all the required parameters such as validation data, validation steps, steps per epoch and number of epochs.

EVALUATION

The CNN and the transfer learning models are trained for 30 epochs with batch size as 32 and the predictions for each of these models are made. The evaluation of the model is done by categorical cross entropy and accuracy matric. Categorical cross entropy is a loss function that is mainly used for image classification. Conventionally, it is done in the form of probability distribution. The loss is defined as $CE=-\Sigma_i t_i \log(s_i)$.

Activation function soft-max is then used. The loss function determines the performance of the model where the gradient is calculated, thus updating the weights and training the hidden attributes. The models are verified by taking the COVID-19 x-rays, training the attributes automatically by the neural net. The images are loaded and the model finally predicts the results as COVID or NON-COVID.

From the table below it is observed that the best performed model is Inception V3 which has achieved an accuracy of 96%. The next best models are VGG16 and Xception with an accuracy [Fig 7,8,9] of 93% and 92% respectively followed by Resnet with 82% accuracy[Table 1].

Tables

TABLE 1. Accuracy for different retrained deep training models for classification of Covid and Non Covid

Model	Accuracy %
VGG16	93
InceptionV3	96
Resnet-50	82
Xception	92

RESULTS

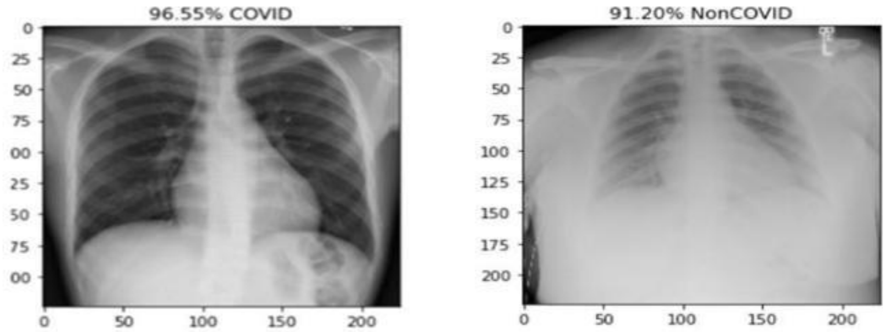

FIGURE 7. Sample Output of one test image for COVID and Non COVID

The sample result using Inception V3 architecture is predicted for a covid sample and a non-covid sample in the above figure. The result displays the percentage of Covid infection or the percentage of how normal it is.

The models are initially trained and tested and are futher used for binary classification. A confusion matric is plotted below for each of the architectures- VGG-16,ResNet-50,Inception V3,Xception. The visualization of confusion matrix reports how well the model predicts the outcome The matrix is divided into 4 regions, they being True Positive, True Negative, False Positive and False Negative.

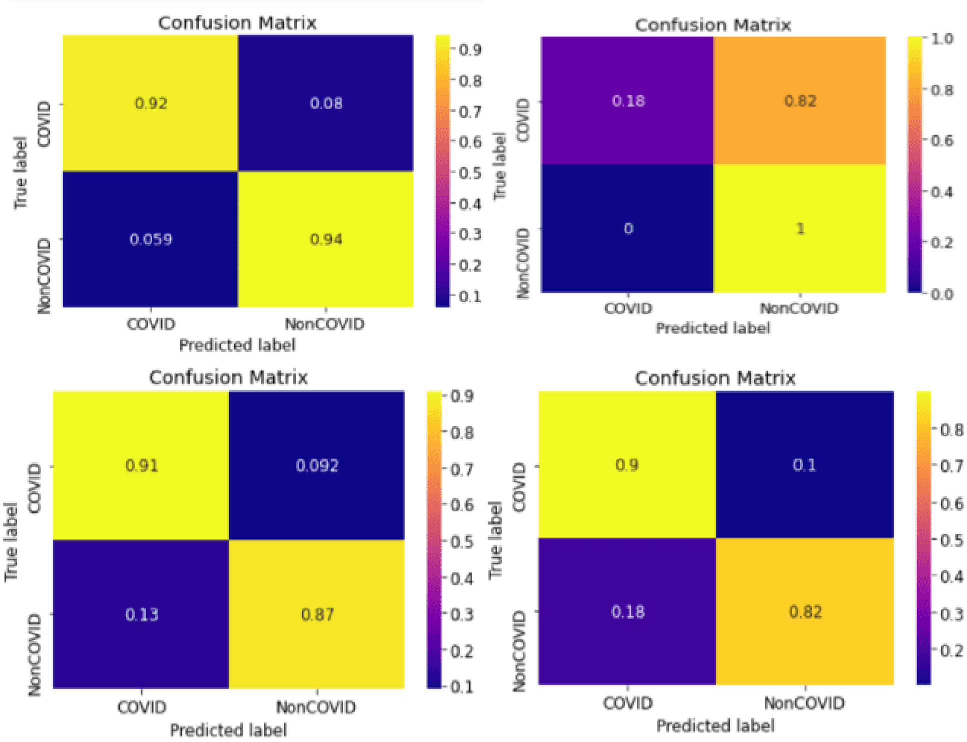

FIGURE 8. Confusion Matrix for Chest X-rays: VGG16, ResNet50, InceptionV3, Xception

	precision	recall	f1-score	support
0	0.93	0.92	0.92	87
1	0.93	0.94	0.94	101
accuracy			0.93	188
macro avg	0.93	0.93	0.93	188
weighted avg	0.93	0.93	0.93	188

	precision	recall	f1-score	support
0	1.00	0.18	0.31	87
1	0.59	1.00	0.74	101
accuracy			0.62	188
macro avg	0.79	0.59	0.53	188
weighted avg	0.78	0.62	0.54	188

	precision	recall	f1-score	support
0	0.86	0.91	0.88	87
1	0.92	0.87	0.89	101
accuracy			0.89	188
macro avg	0.89	0.89	0.89	188
weighted avg	0.89	0.89	0.89	188

	precision	recall	f1-score	support
0	0.81	0.90	0.85	87
1	0.90	0.82	0.86	101
accuracy			0.86	188
macro avg	0.86	0.86	0.86	188
weighted avg	0.86	0.86	0.86	188

FIGURE 9. Classification Reports for Chest X-rays: VGG16, ResNet50, InceptionV3, Xception

A classification report for precision, recall, f1-score and support is generated for the 4 models- VGG16, ResNet50, InceptionV3, Xception.

Precision is nothing but the predictions that have been done rightly to that of all the predictions. The precision is calculated using the formula.

$$Precision= \frac{True\ Positive\ values}{(True\ positive\ values + False\ positive\ values)}$$

The precision ranges between 0 to 1 where 1 means it is perfectly precise. The precision for all the 4 models in given in the classification report.

Recall is how correct prediction is done by the model. It is the ration of true positive values to that of true positive values and false negative values. The recall for all the 4 models is shown in the classification report.

$$Recall = \frac{True\ Positive\ values}{(True\ positive\ values + False\ negative\ values)}$$

The combination of both precision and recall is used to calculate the F-measure. It is gives as

$$F\text{-}Measure = 2 \frac{(* Precision * Recall)}{(Precision + Recall)}$$

The best value for F1 score is 1. It is mainly used to stabilize precision and recall on the positive samples. The F1 score for all the 4 models is shown in the classification report above. F1 score plays a very useful role when the 2 classes are unbalanced.

CONCLUSION

Novel Coronavirus or COVID-19 has affected each one of us in one or the other way. It has also resulted in death in some of the cases. The first and foremost way of detecting the virus is by RT-PCR tests or reverse transcription polymerase chain reaction. But this method is said to be time consuming and results in delayed results.

We have proposed and evaluated four transfer learning models using pre-trained convolutional neural networks models namely VGG16, Inception, Xception and ResNet-50 architectures and used them for classification of the X-rays into COVID or NON-COVID. The performance of each of these models are analyzed and understood. The F1 Score, Recall , Precision and support for each of these models are categorized for each of the architectures in the classification report. The experimental setup showed that by making use of convolutional layers we can automatically extract the hidden parameters in the hidden layer and classify the X-rays in the output stage. Hence, by identifying the virus, we can minimize the risks and impact on health and fight the virus better. It will help us take proper steps and reduce the severity of the virus and make the world covid-free.

In future we would like to expand our scope of research on how the outbreak shoots-up by trying different CNN models. We would also like to work on large datasets, and find out which model performs the best.

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