

COVID-19 Detection using Chest X-Ray Images by Artificial Intelligence

Amey Sanjay Didolkar¹

¹B.E Department of Computer Science and Engineering, G.H.Raisoni College of Engineering-440012, Nagpur, Maharashtra, India

Abstract – The spreading increase in covid-19 patients is overwhelming healthcare systems all over the world. With limited testing kits, every patient with respiratory illness cannot treat using conventional techniques. Deep Learning has boost multi-fold in recent years, and it has played a significant role in image classification, including medical imaging. Convolutional Neural Networks (CNNs) have performed well in detecting many diseases, including coronary artery disease, malaria, Alzheimer's disease, and different dental diseases. The test also has a long turn-around-time and limited sensitivity. The study reveals that infected patients exhibit distinct radiographic visual characteristics, fever, dry cough, fatigue, dyspnoea. Diagnosing possible covid-19 infections on chest X-ray may help high-risk quarantine patients while test results are waiting. X-ray machines are readily available at all the healthcare centers, with no transportation time involved for samples. This project proposes using a chest x-ray to classify the patient's selection for further testing and treatment. The detection is critical acute respiratory syndrome coronavirus responsible for coronavirus disease 2019 (COVID-19), using chest X-ray images has life-saving importance for both patients and doctors. Also, in countries that cannot purchase laboratory kits for testing, this becomes even more vital. This work shows how a change in convolutional layers and an increase in dataset affect classifying performances.

Key Words: COVID-19, Coronavirus, Pandemic, X-Ray, Neural Network, Convolutional Neural Network, Data Science, Artificial Intelligence

1. INTRODUCTION

The ongoing pandemic of Coronavirus or COVID-19 disease 2019-2020 has led to a global health care crisis. The main challenge in this pandemic situation on how to identify COVID-19 patients. Coronavirus or COVID-19 is an infection disease triggered by severe acute respiratory syndrome COVID-19 (SARS-COV2). The coronavirus disease was initially identified in December 2019 in Wuhan, China and has spread globally worldwide. The patient with Pneumonia of the mysterious cause was first reported in the WHO country office in china in December 2019. After the month of December 2019, the disease has spread all over the world. The disease spread very fast, and the number of cases increased highly. Then WHO declared it is a Pandemic. As of 27 Nov. 20, there were – 61308116 Coronavirus cases, 1437835 deaths and 42395359 recovered patients. The number is still rising in the world there were.

Although radiological imaging is not recommended for diagnostics as the patient arrives in the clinic. The chest X-Ray image is useful to observe treatment outcomes and comorbidities in seriously ill patients. The detection of Coronavirus from chest X-Ray and its differentiation from lung disease with indistinguishable opacities is a puzzling function that relies on the accessibility of expert radiologists.

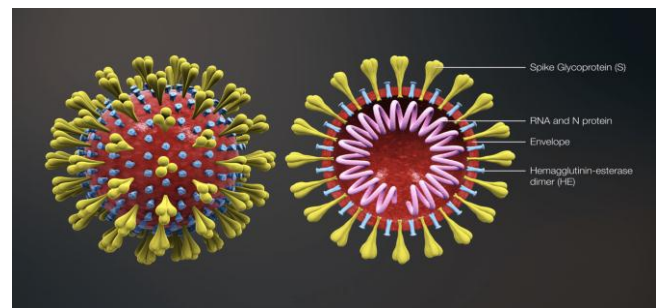


Fig – 1: Novel Coronavirus Structure [1]

All the fragments require to make a new virus assembles under the membrane of the cell. Then the latest virus formation starts from the cell membrane. Each lung has separate segments, called lobes.

Generally, as breath, air moves freely through the trachea. The trachea has three main segments:- first large tube called bronchi, and the second small tubes, called bronchioles and ultimately tiny sacs, is called alveoli. Air passage and alveoli of the trachea are flexible and polymorphic. When breathing, each air sac increases like a small balloon, and when releasing air, the sacs decrease. The alveoli are bounded by small blood vessels on all sides, with the small blood vessels are called capillaries.

Every cell in your body requires essential oxygen to live. When we breathe in the lungs, oxygen is carried into the bloodstream and had throughout your body. In the body's very cell, oxygen is exchanged for a waste gas called carbon dioxide, and then the bloodstream carries this waste gas back to the lungs, where it is disconnected from the bloodstream and then the breath out from the body. Lungs and the respiratory system automatically execute this vital process, called gas exchange. The trachea contains mucus holds the most germs in mucus that pull trachea, bronchi and bronchioles. In a healthy body, the cilia tubes rapidly emit mucus and germs from the trachea. That's their reason for cough. The immune system cells attack viruses and germs that build mucus and cilia and enter alveoli. If the immune system weak, such in a way in the case of coronavirus

infection, then a virus can affect immune cells and bronchiole and alveoli form, which causes your immune system to attack expand viruses. Due to the Infection, alveoli gets fill fluids and making it very difficult for a body to get the oxygen it requires.

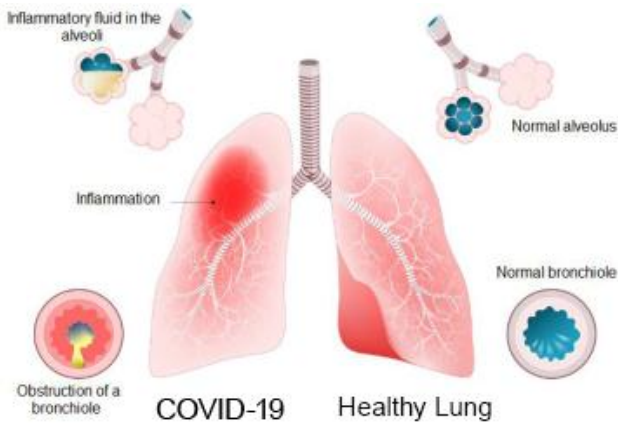


Fig - 2: Coronavirus Diagram

It may create lobar Pneumonia, where one lobe of the lung is affected, or may have bronchopneumonia that affects both lungs' maximum areas. Due to Pneumonia, uneasy to take breathing, fever, cough, Chest pain and coldness, headache, pain and fatigue. It may cause many severe problems like Respiratory failure, which occurs when breathing becomes so tuff a ventilator is required to help breathe. These machines that are save lives, and all the medical equipment companies produce a large amount of upgrading equipment

Recently, survey several researchers have reported using Artificial intelligence-based tools to clear up image classification problems in healthcare, build on training with X-ray images, CT scans, histopathology images, etc. Deep learning is an exceedingly powerful tool for learning complex cognitive problems, and the frequency of their use and assessment in different issues is increasing. In this present study, we have used a deep learning algorithm using the convolutional neural network (CNN) to detect COVID-19 from chest X-ray images for swift diagnosis efficiently.

Due to data scarcity related to COVID-19 chest X-ray images, instead of training the model from scratch, the present study used the "transfer learning method" by leveraging the already available models in solving similar problems. Moreover, transfer learning eases the hypothesis that the training data must be independent and identically distributed with the test data. Coronavirus produces a respiratory infectious disease that has been appearing and spreading very fast, giving rise to a real warning to public health. Transmission rate and mode of transmission are preeminent factors for any contagious disease like Coronavirus. The World Health Organization, respiratory droplets of size significant than 5–10 m act as modes of transmission that potentially involve airborne transmission. What creates an alarming threat to public health as

interaction without necessary safety measures can be highly contagious. This disease poses a high extension factor, with an estimated fatality rate of 2–5%. It shows this spreads very fast with geometric progression. This graph shows the seriousness of the situation. Even after taking so many precautions of wearing masks and maintaining social distancing, the affected patient count increased. It is a matter of hope that the growth factor decreases day by day due to throng consciousness. Early detection of Coronavirus patients is one of the essential aspects to limit the spread of this virus.

World Health Organization listed a few rapid and detailed diagnostic tests for COVID-19 detection, including genesis RTPCR Coronavirus (COVID-19) testing and Cobas SARS-CoV-2 for use Cobas 6800/8800 systems. The COVID-19 tests take a lot of time and money, whereas CNN can play a significant role in automatic positive patient detection. What can save both time and money, which will eventually save life? Moreover, it can add an extra layer of validation as none of the prevailing tests offer 100% accuracy. We would be like to re-emphasize that we do not prefer using the preferring model as an alternative to the conventional diagnostic tests for COVID-19 infection, but as a triage tool to control the suitability of a patient with SARI to undergo the test for COVID-19 infection.

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1.1 OBJECTIVE

The main objective of "COVID-19 Detection using Chest X-Ray Images by Artificial Intelligence" is to facilitate a user-friendly environment for all users and decrease the manual effort. In past days, detection is conducted manually, but we can generate the score and pose the queries automatically in a different resolution of technology. Chest X-Ray imaging technique that plays an essential role in the diagnosis of COVID-19 disease.

2. LITERATURE SURVEY

As of on-going Pandemic covid-19 is a devastating effect all over the world. Day-by-Day cases are going at a higher level breaking its previous day records. Thousands and Lakhs of tests are being conducted, and its cure is yet to be discovered.

In structure to control the spread of covid-19, many suspected cases need to be screened for proper isolation and

treatment. To ease doctors' jobs, radiographic images come into the picture, i.e. X-ray images of the human chest (Lungs) can be used to diagnose the infection. Our computer science and engineering developing branch and building a smart machine reduce the time and effort we take manually. In this AI world, we can detect disease by a computer machine.

Performing tasks that typically require human intelligence can be referred to as AI. Artificial Intelligence (AI) is a rapid technology, made possible by the internet. This may soon have significant impacts on our everyday lives.

Artificial Intelligence in medicine and health care has been a practically hot topic. Artificial Intelligence technology from traditional healthcare technologies can gather data, process it, and give a well-defined output to the end-user. Artificial Intelligence does this through machine learning algorithms and deep learning.

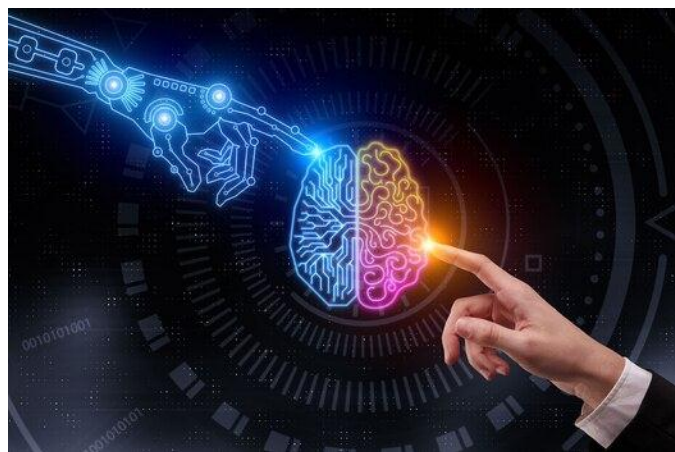


Fig – 3: AI in Medicine [2]

The health-related AI approach's main aim is to analyze the relationship between or treatment techniques and patient outcomes. Artificial Intelligence program is applied to particles such as diagnosis processes, treatment protocol development, patient monitoring and care.

Machine learning or ML is an application of Artificial Intelligence that provides a system with the ability to learn and improve automatically. Machine Learning is well defined in the development of computer programs. The process of learning begins with observation or data. The primary point is to allow the computer to learn automatically without human intervention or assistance. Machine Learning and Deep learning classification techniques can be used to classify whether the suspected patient is infected with the coronavirus (covid-19). Corona Infected Lungs get yellow in color, which makes the X-ray of the chest fade.

Numbers of X-ray images are used to train the Machine Learning and Deep Learning Model and then the model can give more than 90% accuracy in the prediction. This method can be adopted to decide the patient should be shifted to the corona ward with all infected patients or in the separate

ward with the non-infected patients as the symptoms take a minimum of 10-14 days to get on the reports. Radiographic Images would help to diagnose and make a decision on a patient's health.



Fig – 4: AI detect covid-19 in lungs [3]

2.1 MACHINE LEARNING

ML or Machine Learning is a study of computer algorithms that improve automatically through experience. It deals with provision of human intelligence to machine system. For more advanced tasks, it can be challenging for a human to manually create the needed algorithms.

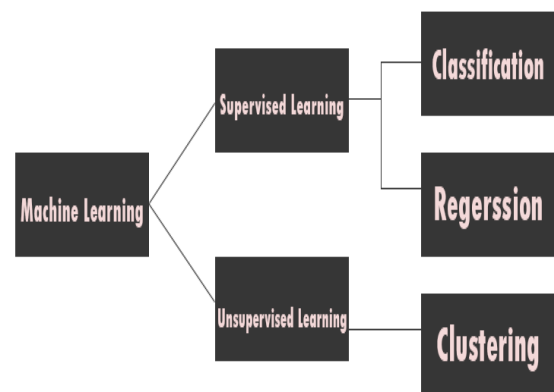


Fig – 5: Machine Learning Techniques

2.2 DEEP LEARNING

Deep Learning is a family of artificial intelligence. Deep Learning has much architecture in them, such as Deep Neural Network, Convolutional Neural Network, and Recurrent Neural Network etc. Deep Learning is a modern variation concerned with an unbounded number of layers of a bounded size that permit practical application and optimized implementation. Deep Learning is also called hierarchical learning or deep structured learning. In artificial intelligence in the healthcare setting, the agency noted that

some deep learning algorithms have already produced transformational outcomes. Deep Learning provides the healthcare industry to analyze data at exceptional speeds without compromising on accuracy. Deep Learning in healthcare has already left its marks. Deep learning could be reducing the admin load while increasing insight into patient care and requirements.

Artificial Intelligence is transforming the operation of medicine. Diagnose diseases from X-Rays and 3D MRI brain images. X-rays are the most used diagnostic imaging test and are widely available.

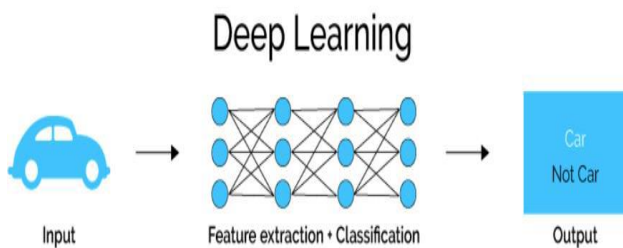


Fig – 6: Deep Learning Technique [4]

2.3 CNN MODEL

In deep learning a (CNN or Convnet) Convolutional neural network is a class of deep neural network is the class of deep neural network most commonly applied to analyzing image. Convolutional Neural Network are regularized version of multilayer perceptions Multilayer perceptions usually means fully connected network that is every one neuron in one layer is connected to all neuron in the a next layer. CNN or Convolutional Neural Network image classification take an input image, process it and classifies it under categories (Eg: Dog, Cat, Car, Medical Field). A computer sets an input image an array of pixels, and it depends on its image resolution. Artificial Intelligence has been observing a monumental growth in bridging the gap between humans and machines' capabilities.

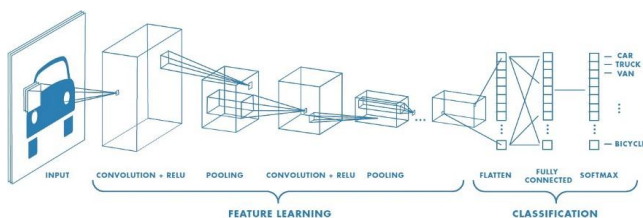


Fig – 7: Convolutional Neural Network [5]

The architecture of a convert is analogous to that of the connectivity pattern of neurons in the human brain and was encouraged by the organization. Deep Learning method utilizing deep convolutional neural networks have been applied to medical image analysis providing promising results. The application covers the whole spectrum of medical image analysis, including Detection, Segmentation, and Classification.

2.4 TRANSFER LEARNING

TL or Transfer Learning is a research problem in (ML) Machine Learning that focal point on storing knowledge obtains while solving one problem and applying it to a different but related problem. It is a favored approach in deep learning where pre-trained models are used as the starting points on computer vision and NLP tasks. Transfer learning or (TL) is an optimization that allows rapid progress or improved performance when modeling the second task. To perform transfer learning with predictive modeling problem that use image data as input. In our project we used transfer learning concept it contain pre-trained class and it will gives much better accuracy.

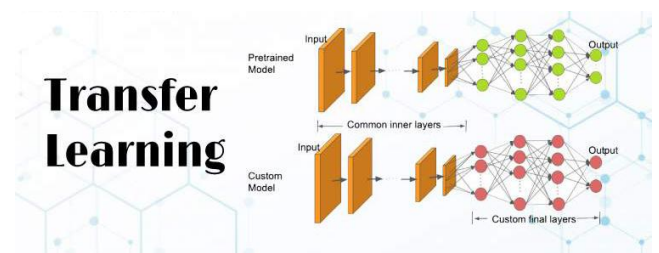


Fig – 8: Transfer Learning [6]

2.5 VGG16

Proposed in 2014 by Simonyan and Zisserman, VGG (Visual Geometry Group) is a convolution neural net (CNN) architecture and used to win ILSVR (ImageNet) competition in 2014. The primary characteristic of this architecture is having a large number of hyperparameters. They concentrated on simple 3×3 size kernels in convolutional layers and 2×2 size in max-pooling layers. At last, it has 2 FC (Fully Connected layers) trailed by a softmax for output. The most familiar VGG models are VGG16, which include 16 layers, respectively. The difference between VGG-16 is that VGG-16 has one more layer in each of the three convolutional blocks.

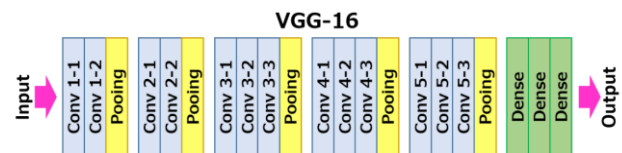


Fig – 9: VGG16 Architecture [7]

2.6 RESNET50

Resnet50 is a deep residual neural networks used for image classification. It is the winner of ILSVRC 2015. The principal innovation is the introduction of the new architecture network-in-network using residual layers. The Resnet50 consists of five steps, each with a convolution and Identity block, and each convolution block has 3 convolution layers, and each identity block also has 3 convolution layers.

Resnet50 has 50 residual networks and accepts images of 224×224 pixels.

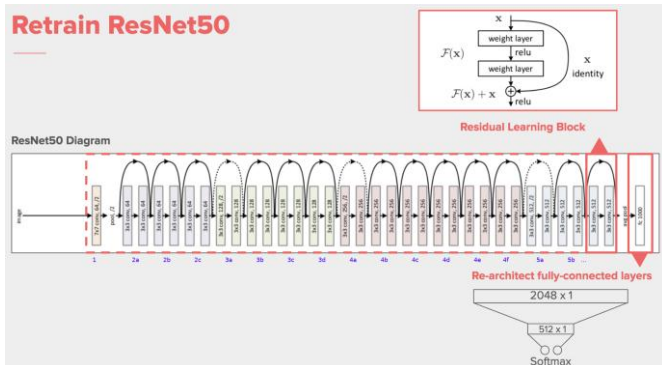


Fig – 10: ResNet50 Architecture [8]

2.7 INCEPTIONV3

Inception models are a type on Convolutional Neural Networks. The inception models differ from the ordinary CNN in the structure where the inception models are inception blocks that mean lapping the same input tensor with multiple filters and concatenating their results. Inception_V3 is new version of inception model presented. It is an improved version of inception_V1 and inception_V2 with more parameters. Indeed, it has block of parallel convolutional layers with 3 different sizes of filters (1x1, 3x3, 5x5). Additionally, 3x3 max pooling is also performed. The outputs are concatenated and sent to a next inception module.

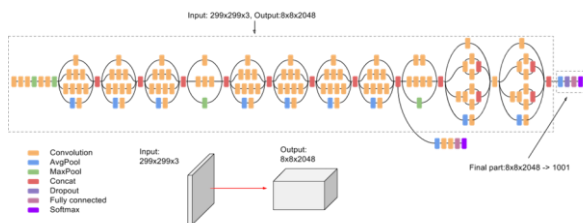


Fig – 11: InceptionV3 Architecture [9]

2.8 DENSENET121

DenseNet201 (Dense Convolutional Network) is a convolutional neural network that is 201 layers deep and accepts an image input size of 224×224 . DenseNet201 is an improvement of ResNet that includes dense connections among layers. It connects each layer to other layer in a feed-forward fashion. Unlike traditional convolutional networks with L layers that have L connections, DensNet201 has $L(L+1)/2$ direct connections. Indeed, compared to traditional networks, DenseNet has can improve the performance by increasing the computation requirement, reducing the number of parameters, encouraging feature reuse and reinforcing feature propagation.

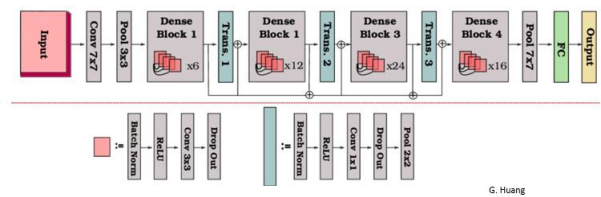


Fig – 12: DenseNet121 Architecture [10]

2.9 XCEPTION

Xception is a (CNN) convolutional neural network that is 71 layers deep. It is an improved version of Inception architecture and involves depth wise separable convolutions. More precisely, Xception replaces the standard Inception modules with depthwise separable convolutions. It showed good results compared to VGG16, Resnet and Inception in classical classification problems. Xception has an image input size of 299x299.

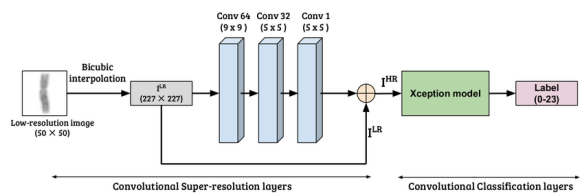


Fig – 13: Xception Architecture [11]

2.10 MOBILENET

MobileNet is a convolutional neural network and an improved version of MobileNet and is made of only 28 layers and has an image input size of 224×224 . Its main characteristic is instead of performing a 2D convolution with a single kernel, instead of performing a 2D convolution with a single kernel uses depthwise separable convolutions that consists in applying two 1D convolutions with two kernels. That means, less memory and parameters required for training and small and efficient model. We can distinguish two types of blocks: first one is residual block with stride of 1, second one is block with stride of 2 for downsizing. For each block, there are layers: the first layer is 1x1 convolution with ReLU6, the second layer is the depthwise convolution and the third layer is another 1x1 convolution but without any non-linearity.

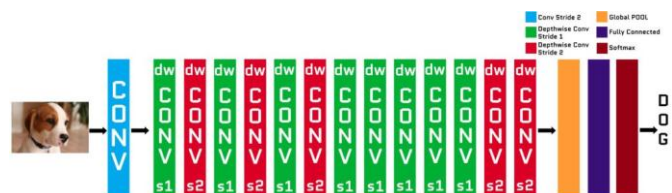


Fig – 14: MobileNet Architecture [12]

3. DATASET COLLECTION

This present work introduces a publicly available image dataset which contains X-Ray. This dataset, named chest X-Ray dataset available in this link, is composed of 1560 images and has two categories 1341 NORMAL and 219 COVID-19. As you can see from Figure 11 that illustrates an examples of chest X-Rays in patients with pneumonia, the normal chest X-Ray shows clear lungs with no zones of abnormal pacification. We use a dataset from Kaggle Dataset to detect Covid-19 Chest X-Ray a front-view chest x-ray.

In the pre-process input images using individual pre-processing techniques. The inspiration behind image pre-processing is to improve the quality of visual details of each input image eliminate or reduce noise present in the original input image, better image quality through increased contrast, remove the low or high frequencies, etc. In this study, we used strength normalization and Contrast Limited Adaptive Histogram Equalization. Intensity normalization is an interesting pre-processing step in image processing applications. In our models, we normalized input images to the standard normal distribution using min-max normalization.

Collecting all chest x- ray images in a super-controlled environment that outcome in high-resolution and super-clean images, although desired, is not always achievable, and as artificial intelligence field progresses, more and more focus is direct toward models and the frameworks that can work reasonably well on variable the resolution, quality, and small-scale labeled datasets. Also the images of Covid-19 class are collect from multiple sources by the original supplier, and some of them may show a dissimilar dynamic range from other ones, but through the training, all the images are normalized to the same distribution to make the model less sensitive to that.



Fig – 15: COVID-19 Chest X-Ray

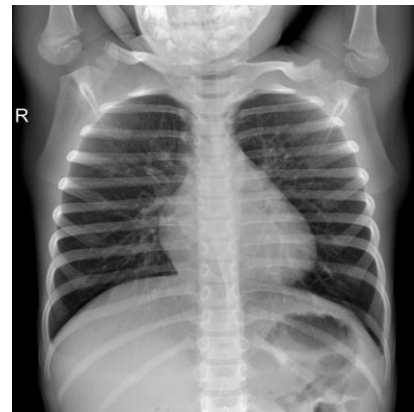


Fig – 16: NORMAL Chest X-Ray

4. DATA AUGMENTATION

The Data augmentation is used for the training process after dataset pre- processing and splitting and has the goal to avoid the risk of over fitting.

Argument	Parameter value
Rescale	1 / 255.0
Rotation range	90
Vertical shift range	0.2
Horizontal shift range	0.2
Shear range	0.2
Zoom range	0.2
Horizontal flip	True
Fill mode	Nearest

After the data pre-processing, splitting and data augmentation techniques are used, our training dataset size is increased and ready to be proceed to the feature extraction step with the proposed models to extract the appropriate and pertinent features. The extracted features from each put forward model are flattened together to create the vectorized feature maps. The cause feature vector is passed to a multilayer perceptron to classify each image into corresponding classes. Finally, the performance of the method is evaluated on test images using the trained model. We repeat each experiment three times and report their average results.

5. TRANSFER LEARNING APPROACH

In a transfer learning model trained on one task is repurposed to another related task, usually by adapting to the new study. For example, one can imagine using an image classification model trained on ImageNet (which contains millions of labeled images) to initiate task-specific learning for COVID-19 detection on a smaller dataset. Transfer learning is mainly useful for tasks where enough training samples are not available to train a model from scratch, such as medical image classification for rare or emerging diseases. This is especially the case for models based on deep neural

networks, which have many parameters to train. Using transfer learning, the model parameters start with already-good initial values that only need some small modifications to be better curated toward the new task. There are two main ways in which the pre-trained model used for a different task. In one approach, the pre-trained model is treated as a feature extractor (i.e., the pre-trained model's internal weights are not adapted to the new task), and a classifier is trained on top of it to perform classification. In another approach, the whole network, or a subset thereof, is fine-tuned on the new task. Therefore the pre-trained model weights are treated as the initial values for the new task, and are updated during the training stage.

6. MODEL TRAINING

All working models are trained with a cross-entropy loss function, which tries to decrease the distance between the predicted probability scores, and the ground truth probabilities.

$$\mathcal{L}_{CE} = - \sum_{i=1}^N p_i \log q_i$$

We can minimize this loss function using a stochastic gradient descent algorithm. We attempted to add regularization to the loss function, but the resulting model did not exhibit better performance.

7. EXPERIMENTAL RESULTS

We fine-tuned each model for ten epochs. The batch size is 08, and the ADAM optimizer is used to optimize the loss function, with a learning rate of 1e-3. All images are down-sampled to 224*224 before being fed to the neural network. All our implementations are done in TensorFlow and are publicly available at <https://github.com/ameyhub/IRJET-COVID-19>

Different metrics are being used for evaluating the performance of classification models, such as classification accuracy, Sensitivity, Precision, and F1-score. Since the current test dataset is highly imbalanced (1341 NORMAL images and 219 COVID-19 images), sensitivity and specificity are two proper metrics which can be used for reporting the model performance.

$$\text{Sensitivity} = \frac{\text{\#Images correctly predicted as COVID-19}}{\text{\#Total COVID-19 Images}}$$

$$\text{Specificity} = \frac{\text{\#Images correctly predicted as Non-COVID}}{\text{\#Total Non-COVID Images}}$$

8. MODEL ARCHITECTURE

Convolutional Neural Network has been playing a great role in categorizing images, in specific medical images. This has

opened new cases of opportunities and made the disease diagnosis much more convenient. It also successfully detects recent novel Corona virus with higher accuracy. One of the restrictions that researchers encounter is a little dataset for training their model. Actually a novel disease, the chest X-ray dataset of COVID-19 positive patients is also limited. Therefore, to avoid over fitting, a sequential CNN model is proposed as in authors' earlier work of [53] for classifying X-ray images. CNN model for COVID-19 detection. This model has 4 main components: input layers, convolutional layers, fully connected layers and output layers.

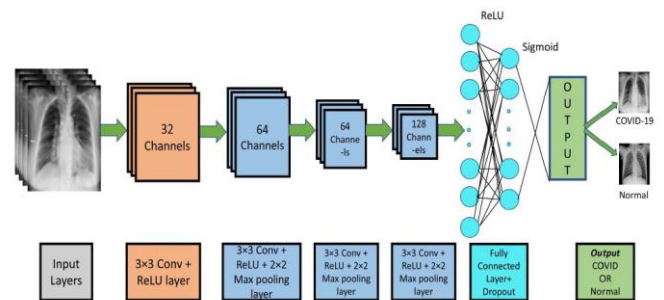


Fig - 17: Workflow diagram of the proposed CNN model for COVID-19 detection. [14]

The tuned data set is sustained into the input layers of a model. It has four CNN layers; first one is the 2D convolutional layer with 3_3 kernels and ReLu activation function. Rectified Linear is the most popular Unit and successful activation functions that are being extensively used in DL. Rectified linear activation does not activate all the neurons at the same time building it computationally systematic in comparison to other activation functions like tan. The next three layers are 2D CNN layer along with the ReLu activation function and Average pooling layer. Average pooling layer assembles the features of the CNN layer by convolving filters over it. It reduces the arithmetic cost as it minimizes the number of parameters thus it helps to avoid over fitting. In each of three layers a Average pooling layer is added after the CNN layer to avoid over fitting and to make the model arithmetic efficient. In the next step, the output of the CNN layers is converted to a long feature vector by a flatten layer. This output from the flatten layer is fed to the fully connected layer with dropout. In a fully join layer, every input neuron is connected to every activation unit of the next layer.

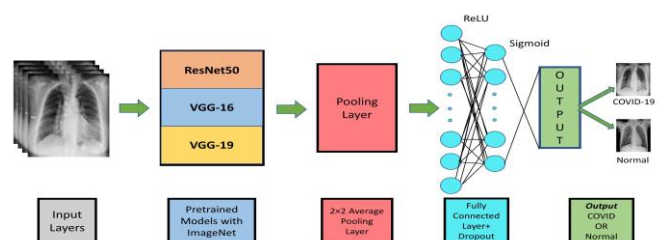


Fig - 18: Workflow diagram of the proposed CNN model for COVID-19 detection. [14]

The input neuron is connected to every activation unit of the next layer in a fully connected layer. The entire input feature is passing through the rectified linear activation function, and this layer categorizes the images to the assigned labels. The sigmoid activation function makes the categorization decision depending on the classification label of the neurons. Finally, the output layer, it is declared if the input X-Ray images.

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

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

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

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

$$F1 = 2 \times \frac{Recall \times precision}{Recall + precision}$$

After extracting the appropriate feature, the last step is to classify the attained data and assign it to a specific class. Among the different classification performance properties, and since our data is balanced, our study uses the following benchmark metrics, including accuracy, sensitivity, specificity, precision and F1 score

9. RESULTS AND DISCUSSION

Accuracy defines how close the cause result is close to the actual value, whereas precision calculates the percentage of the relevant results. The recall is another important factor for evaluating a convolutional neural network model. It gives the percentage of the total applicable results that a model can right classify. The F1-score combines both precision and recall, and it is designated as the weighted average of these two. Even though this is a fine result for the proposed model, a few analysts could realize better results than this with binary classification. However, this work shows how the number of convolutional layers and the number of images in the dataset play a role in the models' performances. As a convolutional neural network classifies images by extracting features from the images, it is practicable to differentiate between images with very minute and subtle changes. The chest X-ray of a COVID-19 patient from the early stage would show distinction from an X-ray of the same patient at the middle and late stages. It provided the necessary dataset. It would be possible to detect the stages of COVID-19 patients. As it is a new disease and a lack of classified data according to different stages, classifying stages are not labeled here in this work, but it is hoped to address this challenge in future work.

10. CLASSIFICATION RESULTS OF THE PROPOSED ARCHITECTURE

This subsection presents and discusses the classification results of chest X-Ray images. Before discussing these results, let us define the two most parameters used in the state of the art of deep learning and computer vision: Train curve is calculate from the training dataset that provides an idea of how well the model is learning. In contrast, the validation curve or test curve is calculated from a hold-out validation dataset that provides an idea of how well the model is generalizing.

10.1 VGG16

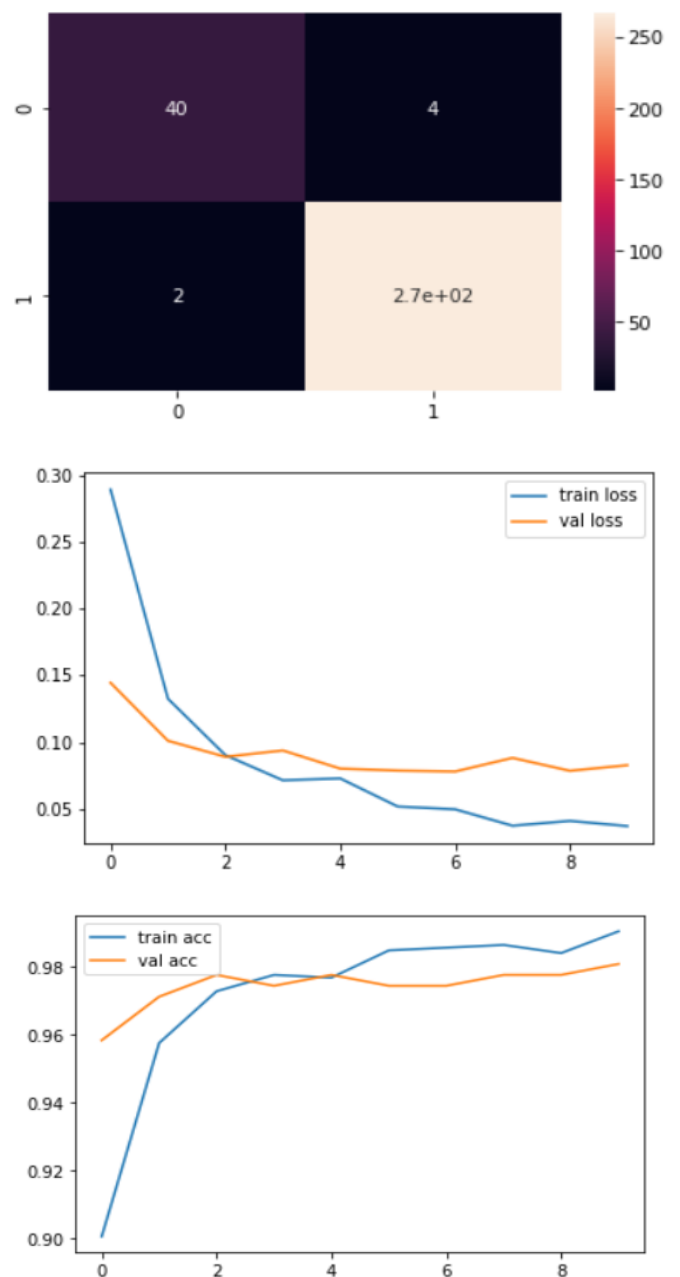


Fig – 16: Accuracy and loss curve and confusion matrix of VGG16

In figure shows the accuracy and loss curve and confusion matrix of VGG16. For the train and test accuracy and epoch 0 to epoch, we can observe that the accuracy increases until the value 97.28 %. After epoch 5 the accuracy starts to be stable, equal to 97.68 % and 98.48 % for training data and test data.

A good fit can be observed for the loss curve of train data in either the quick increasing interval from epoch 0 to epoch 10 where the loss, or in the other interval, where the decrease is slow and converges.

(0) Represent as NORMAL and (1) Represent as COVID-19

As shown in the confusion matrix, for the COVID-19 class, the model was able to identify 266 images as COVID-19 and 2 images as Normal. It can be seen that for images class (Normal), the VGG16 model was able to predict 40 images as Normal and 4 as COVID-19

COVID-19

Precision - 0.98

Recall - 0.91

F1-Score - 0.93

NORMAL

Precision -0.99

Recall - 0.99

F1-Score - 0.99

Accuracy Score - 98%

10.2 RESNET50

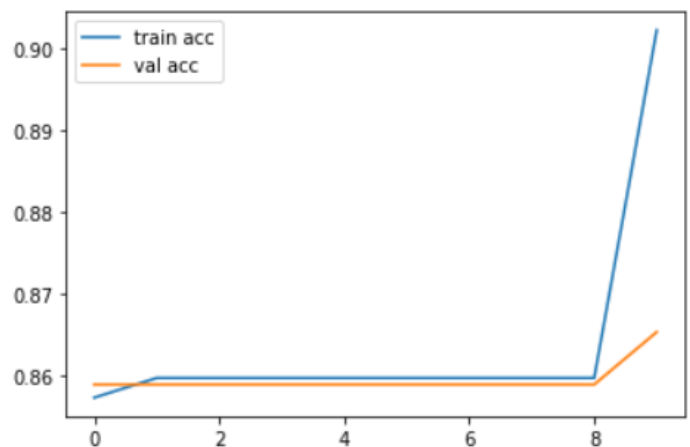
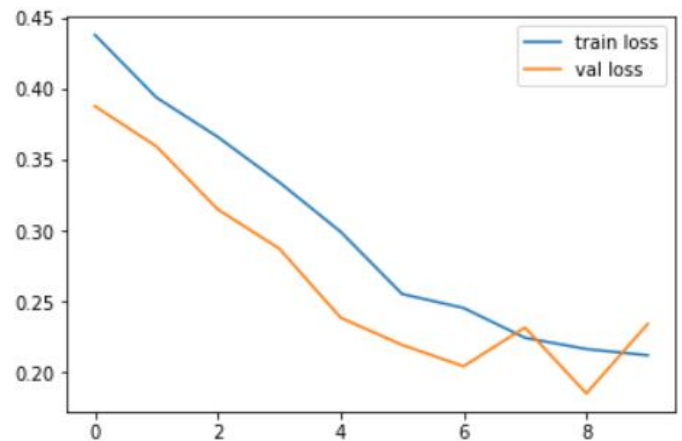
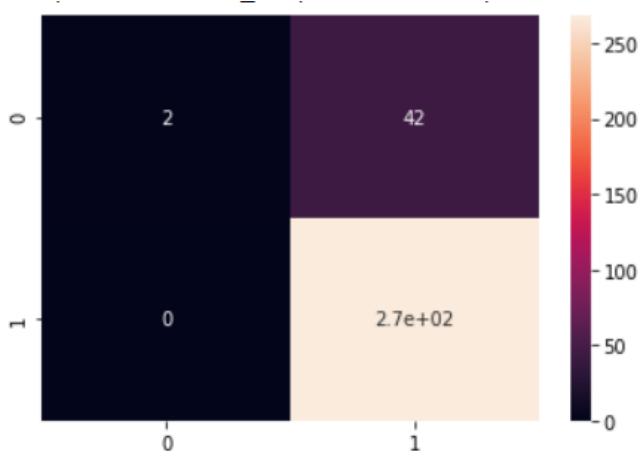


Fig - 17: Accuracy and loss curve and confusion matrix of ResNet50

In figure shows the accuracy and loss curve and confusion matrix of ResNet50. For the train and test accuracy and epoch 0 to epoch, we can observe that the accuracy increases until the value 85.98 %. After epoch 5 the accuracy starts to be stable, equal to 85.98% for training data and test data.

A good fit can be observed for the loss curve of train data in either the quick increasing interval from epoch 0 to epoch 10 where the loss, or in the other interval, where the decrease is slow and converges.

(0) Represent as NORMAL and (1) Represent as COVID-19

As shown in the confusion matrix, for the COVID-19 class, the model was able to identify 268 images as COVID-19 and 2 images as Normal. It can be seen that for images class (Normal), the ResNet50 model was able to predict 2 images as Normal and 42 as COVID-19

COVID-19

Precision - 1.00

Recall - 0.05

F1-Score - 0.09

NORMAL

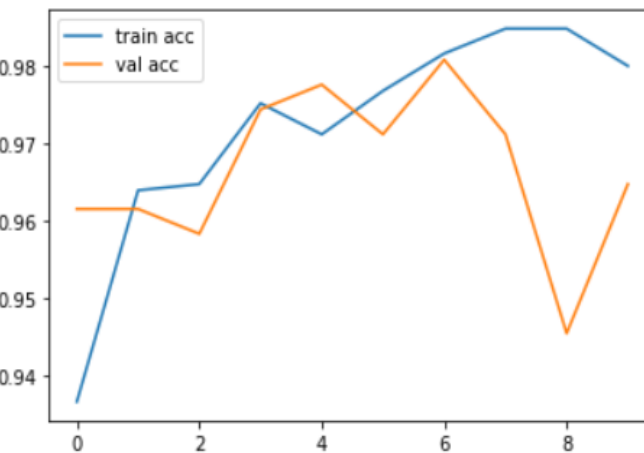
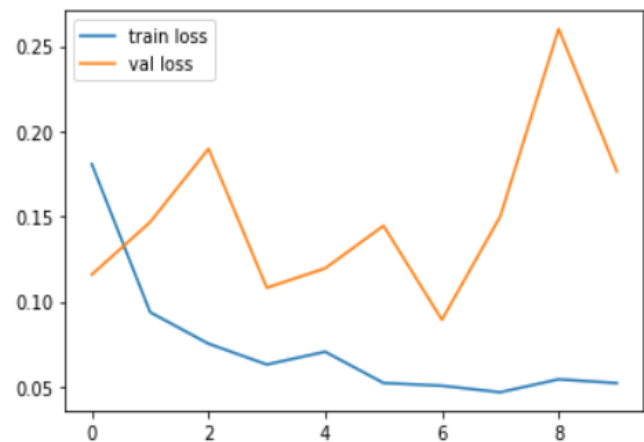
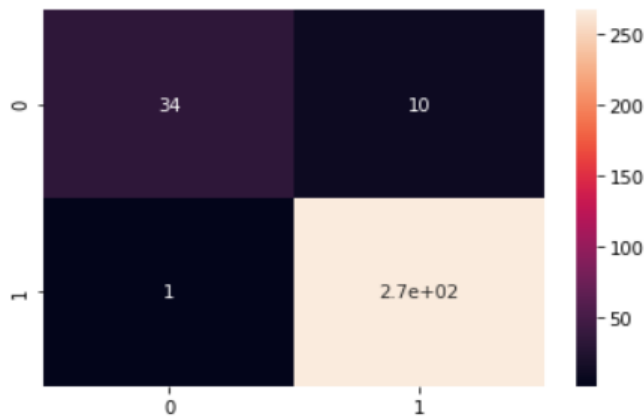
Precision -0.86

Recall - 0.01

F1-Score - 0.93

Accuracy Score - 86%

10.3 INCEPTIONV3



In figure shows the accuracy and loss curve and confusion matrix of InceptionV3. For the train and test accuracy and epoch 0 to epoch, we can observe that the accuracy increases until the value 96.47 %. After epoch 5 the accuracy starts to be stable, equal to 97.12 % and 98.16 % for training data and test data.

A good fit can be observed for the loss curve of train data in either the quick increasing interval from epoch 0 to epoch 10 where the loss, or in the other interval, where the decrease is slow and converges.

(0) Represent as NORMAL and (1) Represent as COVID-19

As shown in the confusion matrix, for the COVID-19 class, the model was able to identify 267 images as COVID-19 and 1 images as Normal. It can be seen that for images class (Normal), the InceptionV3 model was able to predict 10 images as Normal and 34 as COVID-19

COVID-19

Precision - 0.97

Recall - 0.77

F1-Score - 0.86

NORMAL

Precision -0.96

Recall - 1.00

F1-Score - 0.98

Accuracy Score - 96%

10.4 DENSENET121

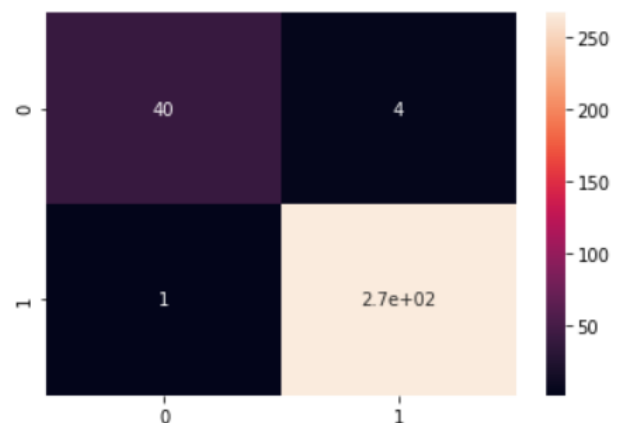
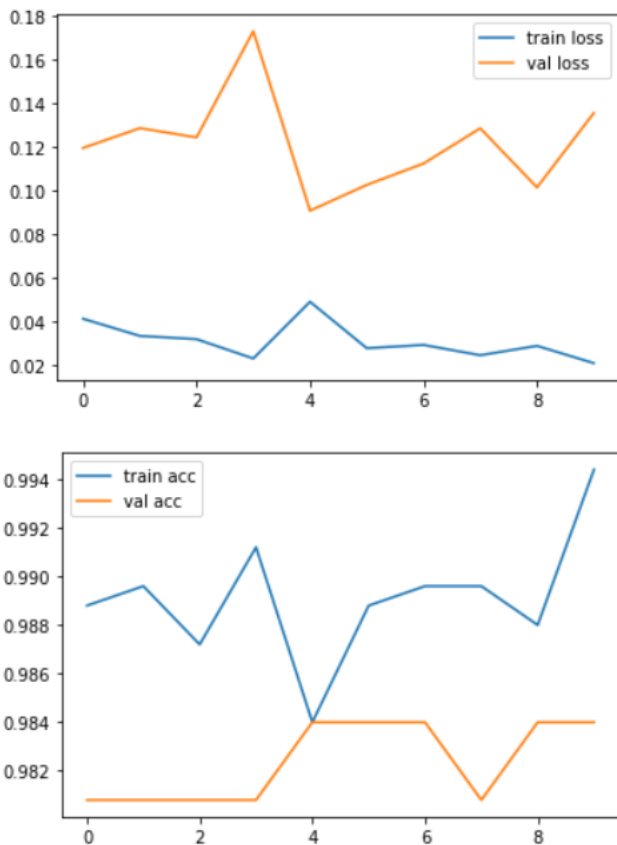


Fig - 18: Accuracy and loss curve and confusion matrix of inceptionV3



NORMAL

Precision - 0.99

Recall - 1.00

F1-Score - 0.99

Accuracy Score - 98%

10.5 XCEPTION

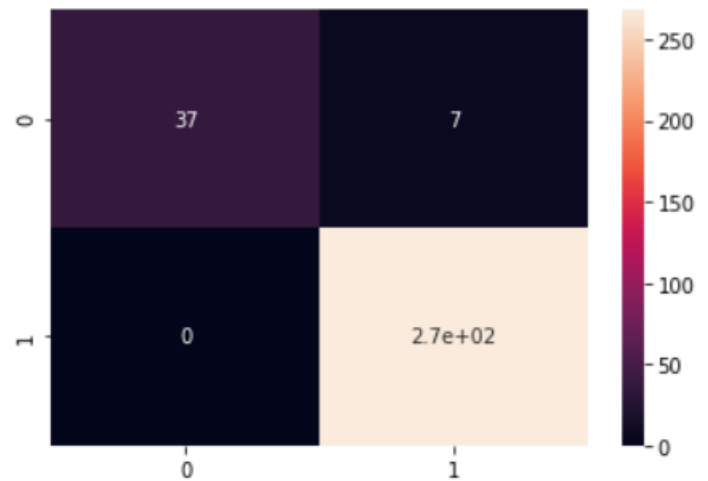


Fig - 19: Accuracy and loss curve and confusion matrix of DenseNet121

In figure shows the accuracy and loss curve and confusion matrix of DenseNet121. For the train and test accuracy and epoch 0 to epoch, we can observe that the accuracy increases until the value 98.72 %. After epoch 5 the accuracy starts to be stable, equal to 98.40 % and 98.96 % for training data and test data.

A good fit can be observed for the loss curve of train data in either the quick increasing interval from epoch 0 to epoch 10 where the loss, or in the other interval, where the decrease is slow and converges.

(0) Represent as NORMAL and (1) Represent as COVID-19

As shown in the confusion matrix, for the COVID-19 class, the model was able to identify 267 images as COVID-19 and 1 images as Normal. It can be seen that for images class (Normal), the DenseNet121 model was able to predict 40 images as Normal and 4 as COVID-19.

COVID-19

Precision - 0.98

Recall - 0.91

F1-Score - 0.94

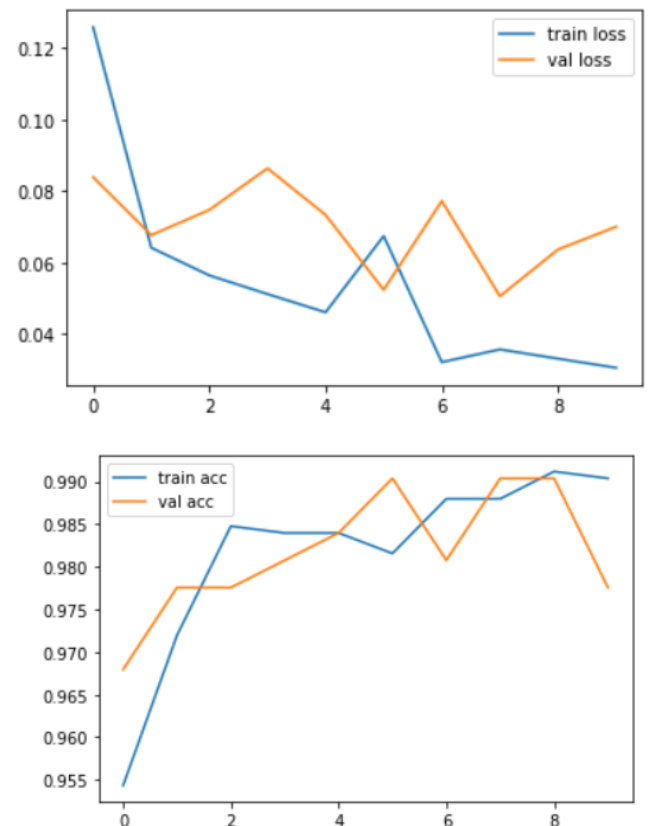


Fig - 20: Accuracy and loss curve and confusion matrix of Xception

In figure shows the accuracy and loss curve and confusion matrix of Xception. For the train and test accuracy and epoch 0 to epoch 10, we can observe that the accuracy increases until the value 98.48 %. After epoch 5 the accuracy starts to be stable, equal to 98.40 % and 98.80 % for training data and test data.

A good fit can be observed for the loss curve of train data in either the quick increasing interval from epoch 0 to epoch 10 where the loss, or in the other interval, where the decrease is slow and converges.

(0) Represent as NORMAL and (1) Represent as COVID-19

As shown in the confusion matrix, for the COVID-19 class, the model was able to identify 268 images as COVID-19 and 0 images as Normal. It can be seen that for images class (Normal), the Xception model was able to predict 37 images as Normal and 7 as COVID-19.

COVID-19

Precision – 1.00

Recall – 0.84

F1-Score – 0.91

NORMAL

Precision –0.97

Recall – 1.00

F1-Score – 0.99

Accuracy Score – 97%

10.6 MOBILENET

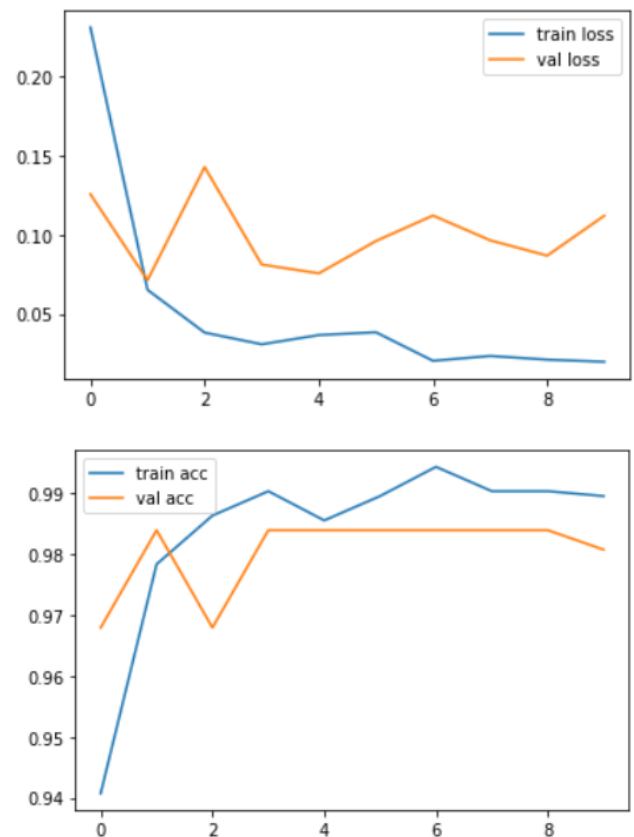
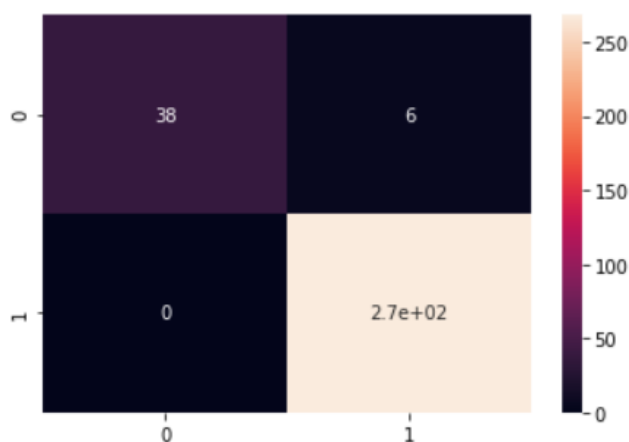


Fig – 21: Accuracy and loss curve and confusion matrix of MobileNet

In figure shows the accuracy and loss curve and confusion matrix of MobileNet. For the train and test accuracy and epoch 0 to epoch 10, we can observe that the accuracy increases until the value 98.64 %. After epoch 5 the accuracy starts to be stable, equal to 99.04 % and 99.44 % for training data and test data.

A good fit can be observed for the loss curve of train data in either the quick increasing interval from epoch 0 to epoch 10 where the loss, or in the other interval, where the decrease is slow and converges.

(0) Represent as NORMAL and (1) Represent as COVID-19

As shown in the confusion matrix, for the COVID-19 class, the model was able to identify 268 images as COVID-19 and 0 images as Normal. It can be seen that for images class (Normal), the MobileNet model was able to predict 38 images as Normal and 6 as COVID-19.

COVID-19

Precision – 1.00

Recall – 0.86

F1-Score – 0.09

NORMAL

Precision – 0.98

Recall – 1.00

F1-Score – 0.99

Accuracy Score – 98%

Model Name	Sensitivity	Specificity
VGG16	0.90	0.99
ResNet50	0.04	1.00
InceptionV3	0.77	0.99
DenseNet121	0.90	0.99
Xception	0.84	1.00
MobileNet	0.86	1.00

11. CONCLUSION & FUTURE SCOPE

This study has preferred a deep learning-based model to detect COVID-19 cases from chest X-Ray images. The detection of COVID-19 plays an essential role in preventing the spread of this global pandemic. The results look promising as such from the size of the publicly available dataset is small. We use the Convolutional neural network model to perform the detection that we trained with the dataset with the total images of 219 COVID-19 and 1341 Normal patients. We use (VGG16, ResNet50, InceptionV3, MobileNet, Xception, and DenseNet121) to predict accuracy. The accuracy and F1-Score of the model are of (98%, 86%, 96%, 98%, 97%, and 98%). Through the small dataset, we get the F1-Score. If we improve further with a multi-class classification and the availability of a large dataset, we can get the best result. Finally, Convolution Neural Network has excellent success in detecting COVID-19 with minimal time, Resource and cost. Such a highest accuracy, the success of a model it is not clinically tested. Such a high accuracy will play an essential role in detecting fast COVID-19 patients, thus reducing the people's testing time and cost.

The COVID-19 challenges are somehow uncover the drawback related to AI. The existing form of AI, in the form of machine learning and deep learning is trying to identify different pattern in the training databases. AI can provide sufficient results just in case having enough data for training and testing different systems with several approaches.

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BIOGRAPHIES



Amey Didolkar

LinkedIn:

<https://www.linkedin.com/in/amey-didolkar-ba1490140/>

Github: <https://github.com/ameyhub>