Covid-19 infected lung detection .
Using machine Learning

by

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

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Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
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Abstract

In every 100 years, there has been a pandemic all around the world. The globe faced Plague, Cholera, and Spanish Flu in the years 1720, 1820, and 1920, respectively. Coronavirus, commonly known as Covid-19, is currently circulating in 2020. Coronavirus affects the nose, sinuses, upper neck, and lungs, among other parts of the human respiratory system. Coronaviruses come in a variety of types, although the majority of them aren't harmful. A brand-new coronavirus epidemic occurred in the Chinese city of Wuhan in December 2019. It was first recognized as SARS-CoV-2 by the World Health Organization, then renamed Covid-19, and it spread swiftly over the world by March 2020. The novel COVID-19 has the potential to develop an infection of the respiratory system. In both the upper and lower respiratory tracts, it can affect the sinuses, nose, throat, windpipe, and lungs.COVID19 is a virus that infects humans via respiratory droplets, coming into contact with a positive for COVID19patientCOVID-19 detection is one of the most challenging undertakings in the globe owing to the virus's fast spread. The number of persons diagnosed with COVID-19 is increasing dramatically, according to data, with over 16 million confirmed cases. For our research, we're looking for COVID-19 symptoms in patients' chest X-ray pictures. We began by gathering information from a variety of sources and categorizing it as COVID-19 positive, other lung illnesses, and normal chest X-ray pictures. Second, we used VGG16, InceptionV3, and ResNet50 to classify the data. The accuracy rates for VGG16, ResNet50, and InceptionV3 were 97.82 percent, 98.89 percent, and 97.65 percent, respectively. Then we combined these classifiers into an ensemble model, and COVDet19 V1 attained an overall accuracy of 97.92 percent.

Keywords: COVID-19, Corona Virus, Deep Neural Network, VGG, Inception V3, ResNet, Ensamble Modeling, VGG16, ResNet50.

Dedication (Optional)

A dedication is the expression of friendly connection or thanks by the author towards another person. It can occupy one or multiple lines depending on its importance. You can remove this page if you want.

Acknowledgement

Firstly, all praise to the Great Allah for whom our thesis have been completed without any major interruption.
Secondly, to our co-advisor Md. Ashraful Alam sir for his kind support and advice in our work. He helped us whenever we needed help.
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Chapter 1

Introduction

1.1 Motivation

To survive and develop as social creatures, we rely significantly on collaboration. COVID-19, on the other hand, poses a serious danger to our ability to socialize in order to earn a living. COVID-19 is mostly transmitted through air. By being cautious and avoiding social activities, we can prevent COVID19 from spreading. But how long can countries like Bangladesh, India and the Maldives avoid social events due to their overpopulation? It's quite hard to stop COVID-19 from spreading. Since December 2019, COVID-19 has infected 320 million individuals and killed 5.52 million of them. Furthermore, the COVID-19 virus continues to mutate and emerge with new variations, resulting in an increase in mortality and a pace of transmission that is shattering all prior records. As a consequence of the increasing number of persons seeking COVID-19 testing at hospitals and clinics, hospitals and clinics are struggling to test and deliver tests on time. Due to the immense demand, hospitals and clinics are having difficulty preparing findings, and they are running out of time by a day or two. Patients who are badly impacted by COVID-19, on the other hand, may notice that their health is worsening as the virus wreaks havoc on their lungs. Furthermore, the most popular COVID-19 test is a PCR (polymerase chain reaction) test, which detects the presence of infection antibodies.The PCR test is costly and requires great accuracy; it also takes one or two days to provide a result, with a significant risk of false negatives[18].As a result, if the virus is not discovered quickly enough, or if reports imply that it is positive when it is not, the virus might have far-reaching repercussions, making it impossible for governments to regulate its spread. Again, many overcrowded nations lack the capacity to administer COVID-19 exams and testing centers for huge populations. However, these problems may be readily solved by using radiography chest image analysis, which is a popular alternative to the PCR test. Artificial Intelligence (AI) has been widely embraced and employed in medical picture categorization applications due to its high accuracy achieved through deep learning. As a result, Artificial Intelligence (AI) might be a good fit for assessing radiography chest pictures of COVID-19-affected lungs. [14]. The UN Global Pulse conducted a study on the use of AI to COVID-19, which found[38] that AI has a lot of promise for human accuracy and can save radiologists time and effort. Using X-ray images of infected lungs from COVID-19 to diagnose COVID-19 is the less expensive and faster option. Machine learning is showing promising outcomes in statistical learning, data processing, and artificial intelligence in medicine [12]. As a result, artificial intelligence (AI) and deep learning may be utilized to enhance COVID-19 detection and identification. As a consequence, CT scans and X-ray pictures may be transmitted, and the findings of COVID-19 PCR tests will be delivered faster. Therefore, we're working on a system that can recognize COVID-19 from diseased lungs X-ray pictures using the quickest binary classification of COVID-19, then compare them to normal chest X-ray images.

1.2 Aims and Objectives

The objective is to develop a deep learning model that can predict the COVID-19 test's outcome. Our major objective is to demonstrate the COVID-19 classification result as well as to grasp the underlying classification parts. Understanding the significance of traits might help future studies do better.

1.3 History of COVID-19

Wuhan is a place in central China where the first COVID-19 was discovered in December of this year. For starters, it was stated that a large number of patients were taken to Wuhan hospitals due to pneumonia. Doctors assumed it was just regular pneumonia caused by a coronavirus. However, when the number of victims grew, they reconsidered and discovered that this coronavirus is an entirely new type of virus known as SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2). Later they named it COVID-19. This virus is highly contagious for humans and it is one kind of Baltimore class IV single-stranded RNA virus. When it infected humans, it remained silent for 5-12 days.It causes symptoms in the human body later on, and the infection lasts for 7-14 days. COVID-19 is a virus that transmits quickly and sustainably from one person to another by the COVID-19 infected individual's breathing, coughing, sneezing, and talking. The new COVID-19 has the potential to cause a respiratory tract infection. It can also affect the sinuses, nose, throat, windpipe, and lungs in both the upper and lower respiratory tracts. COVID-19 is a virus that infects humans by respiratory droplets, coming into contact with a COVID-19 positive patient, and contacting the surface of COVID-19 virus-infected things. This virus travels mostly via the air and may survive in congested indoor environments such as restaurants, public transportation, hospitals, educational institutions, or any form of social gathering for up to three hours, infecting hundreds of individuals at once. The vast majority of virus-infected persons will experience mild to moderate sickness and will be able to recover without therapy. Some, on the other hand, will get extremely unwell and require medical attention. Adults with major diseases, such as depression, diabetes, chronic respiratory disease, or cancer, are at a higher risk of becoming. COVID-19 may make anyone sick, and at any age, they can get severely sick or die. COVID-19 infection symptoms include loss of smell and taste, fever, cough, and breathing problems. Furthermore, COVID-19's fast spread throughout the world prompted the World Health Organization (WHO) to declare it a Public Health Emergency of International Concern in January 2020. Later, the overall number of COVID-19 positive patients and the death rate in every nation across the world were so alarming that the World Health Organization proclaimed it a global pandemic in March 2020. COVID-19 sufferers numbered approximately 320 million individuals globally as of early December 2021, with more than 5.52 million people dying as a result of the virus, however the true figure might be significantly higher.

1.4 Research Methodology

As we progress through the procedure, we discover that detecting COVID-19 using precise and low-cost detection techniques is difficult. Machine learning models such as VGG16, ResNet50, and InceptionV3 have been trained. In the first stage, we pre-processed the CT-scan image data into a well-defined form of 224*224*3. The data was then divided into three groups: COVID-19 positive, other pneumonia, and normal X-ray pictures of the lungs. Then we fed this data into machine learning models, which we trained and assessed, and used them to construct several ensembles. Finally, the performances of various groups are compared.

1.5 Research Orientation

We discussed previous research relating to our topic field by other researchers in Chapter 2. Then, in Chapter 3, we demonstrated and described the algorithms, convolution layer, and activation functions that we used in our studies. In Chapter 4, we also showed how we put our work into practice and how our datasets were distributed. In Chapter 5, we detailed the findings of our investigation once more. Finally, in Chapter 6, we came to a conclusion and discussed future prospects as well as connected topics.

Chapter 2

Literature Review and Related Work

2.1 Literature Review

COVID-19 is a sickness produced by severe acute respiratory syndrome (SARS) that can cause illness of the lungs.It transmits in almost the same manner which other groups of viruses do, usually via direct person-to-person contact. Diseases can indeed be minor or fatal. The symptoms of an infectious disease are generally mild, similar to those of a respiratory illness. COVID-19, on the other hand, is a virus that has never been seen in humans, which means that anyone can be infected and that no one is immune to it[28].Severe acute respiratory disease can cause serious illnesses, Middle East respiratory syndrome (MERS) and sudden acute respiratory syndrome (SARS) are two examples (SARS).The bulk of illnesses we experience each year are caused by different virus infections, which aren't as dangerous to some of the more healthy individuals[17].

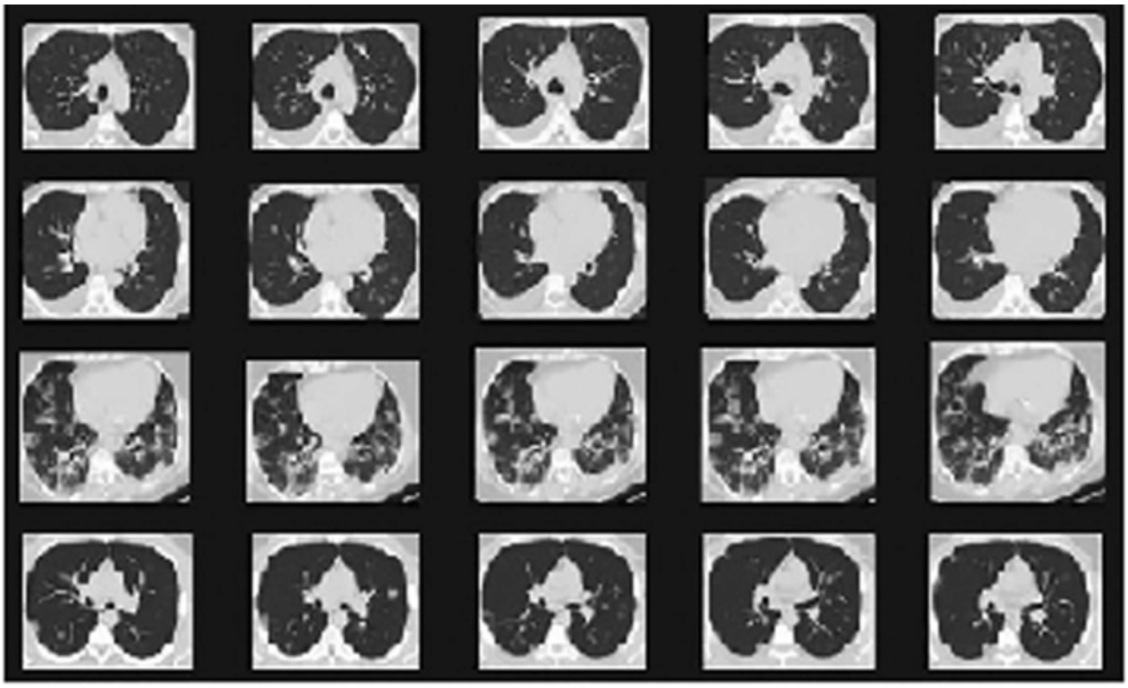
2.2 Related Works

As Coronavirus has become the new problem in the world, experts are trying to recover the diseases fully. Previously some Deep learning methods in medical analysis have worked superbly. Some of the methods were, 1. X-Rays, 2. CT- scans. CXR in COVID-19 is used to identify the major reasons and types of respiratory variation from the standard, as well as to create the medical network. In comparison to CT, CXR is a rather sensitive tool for detecting COVID-19 lung illness, with a reported baseline CXR a electability of 69 percent [26] .Chowdhury et. al. [21] employed a CNN to create their diagnosis model using chest x-rays. CNN is a neural network model which enables us to obtain hierarchical interpretations for the picture material.[16] Some pre-trained networks were used like ResNet, DenseNet121, InceptionResnetV2, DenseNet201, Resnet50, MobilenetV2, InceptionV3, VGG16, VGG19, and CNN. Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun introduced ResNet (Residual Network) as a form of neural network in their paper "Deep Residual Learning for Image Recognition " in 2015. [13] ResNet has achieved accuracies of 96%, 99%, and 91%. [27][23][33] Next DenseNet which is a convolutional neural network whereby each level is linked to other levels lower in the system;

for example, the very first layer connects to the second, third, fourth, and etc., while the second layer is connected to the third, fourth, fifth, and etc. [29] Li et al have been using DenseNet121 on an entire sample of 429 x-ray pictures and accomplished an 88 recognition rate with only an AUC score of 0.97.[28] Rahaman et al looked at fifteen different pre-trained CNN models and found that VGG-19 had the best classification accuracy of 89.3 percent.[31] InceptionResnetV2, DenseNet201, Resnet50, MobilenetV2, InceptionV3, VGG16, and VGG19 was used by Asnaoui and Chawki [22] where InceptionResnetV2 accrued 92.2% accuracy. In some of the previous work it is proved that CT scans give less false results. In CT- scan you cannot surely say if it is a positive result or negative. You can assume that it might be positive with other possible diseases like pneumonia, infection etc. Wu et al. [34] used several CNN models to identify COVID-positive patients from Computed tomography pictures. Wang suggested a 3-dimensional DCNN (DeCovNet) to identify COVID-19 employing Computed tomography segments. To identify COVID-19, He et al [24] presented a database containing just a few hundred pictures of lungs Computed tomography and devised a method called Self-Trans. Another method, 3D CT scans by Zheng et al [34]te was introduced where a pre-trained U-Net was used to divide 3D lung data, and a DL approach was then deployed with them to anticipate infected areas and the accuracy was 95.9%. Again another work was introduced using picture labeling, this was possible to perceive and localize tumors on COVID-19 and pneumonia CT images. It was introduced by Hu et al [25]. It gave 89% accuracy. Roberts et al [43]Discovered a method where lung segmentation has been employed in which was before phase in a variety of models, and computer models have incorporated learning algorithms with just an ImageNet-trained system. Sarker et al [30] used DenseNet121 and gained 87% accuracy. Another method is COVNet which has the aim of extensive genome-wide association studies (GWAS) to share similar and unusual germline genetic variations linked to extreme or deadly COVID-19 genetic predisposition. [40] This method was introduced by Li et al [46] with 95% accuracy. The next model was called DeepPneumonia which gave AUC of 0.99. It was introduced by Yang. This model also offers the localization of both the major lesion traits, namely ground-glass opacity. The next method gathered all chest x-rays and lungs CT scans pictures and did CNN and developed AlexNet. This was discovered by Maghdid et al [42]. After lungs separation of aberrant Computed tomography segments, a two-layer fully connected neural network was utilized to group segments altogether, preceded by such an EfficientNet B4 deeper CNN architecture was another one which was discovered by Bai et al [19].
Shah et al [44] offered an approach that relies on a CNN with just an efficiency of 82.1 percent and 5 transmission models, including VGG-19 outperforming everybody with an efficiency of 94.52 percent. A COVIDx-CT set is generated utilizing the GSInquire platform, which includes feature extraction and preparation in a format appropriate for comparison, as well as efficiency testing and assessment.[15] In [39], present a summary of newly invented deep learning algorithms that use several clinical imaging methods including Computed tomography and X-ray. To address the shortcomings of previous algorithms, this research proposes a methodology centered on domain adaptation for classifying COVID-19 infected people.

2.3 Coronavirus Detection

Because the disease swept around the planet in springtime 2020, clinical tests for COVID-19 have risen exponentially. According to ongoing study, lung Computed tomography and x-rays are quite often insufficient to detect or rule out COVID-19 according to their own. Computed tomography or x-rays, when combined alongside blood testing, health information, and a medical examination, can diagnose COVID-19 or determine the severity of symptoms in some patients.



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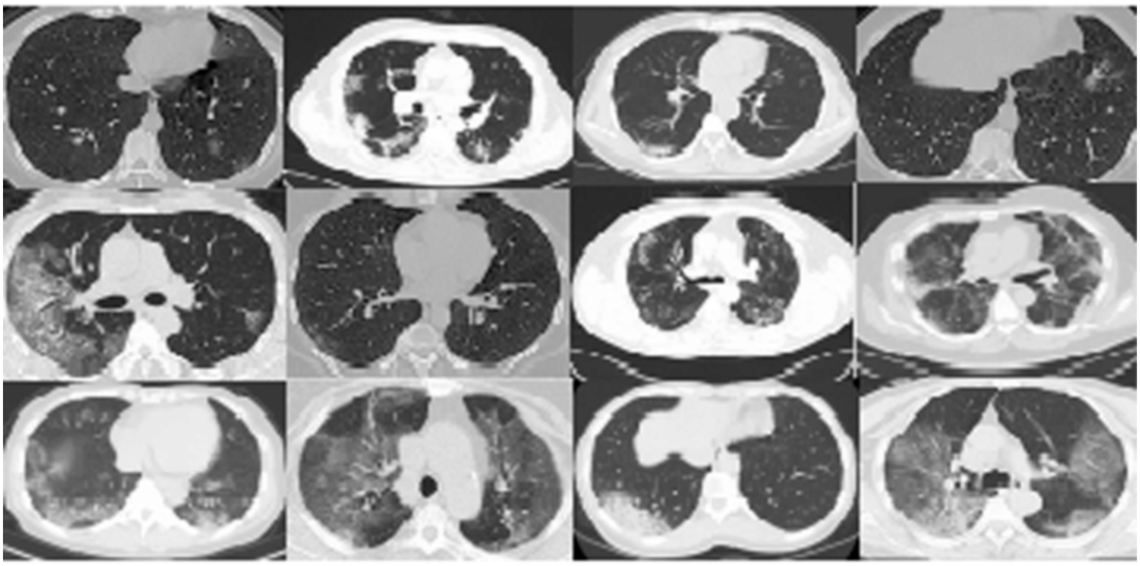

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Figure 2.1: COVID-19-positive pictures from the SARS-CoV-2 CT scan sample and the COVID-CT database

Chapter 3

Research Methodology:

3.1 Research Methodology:

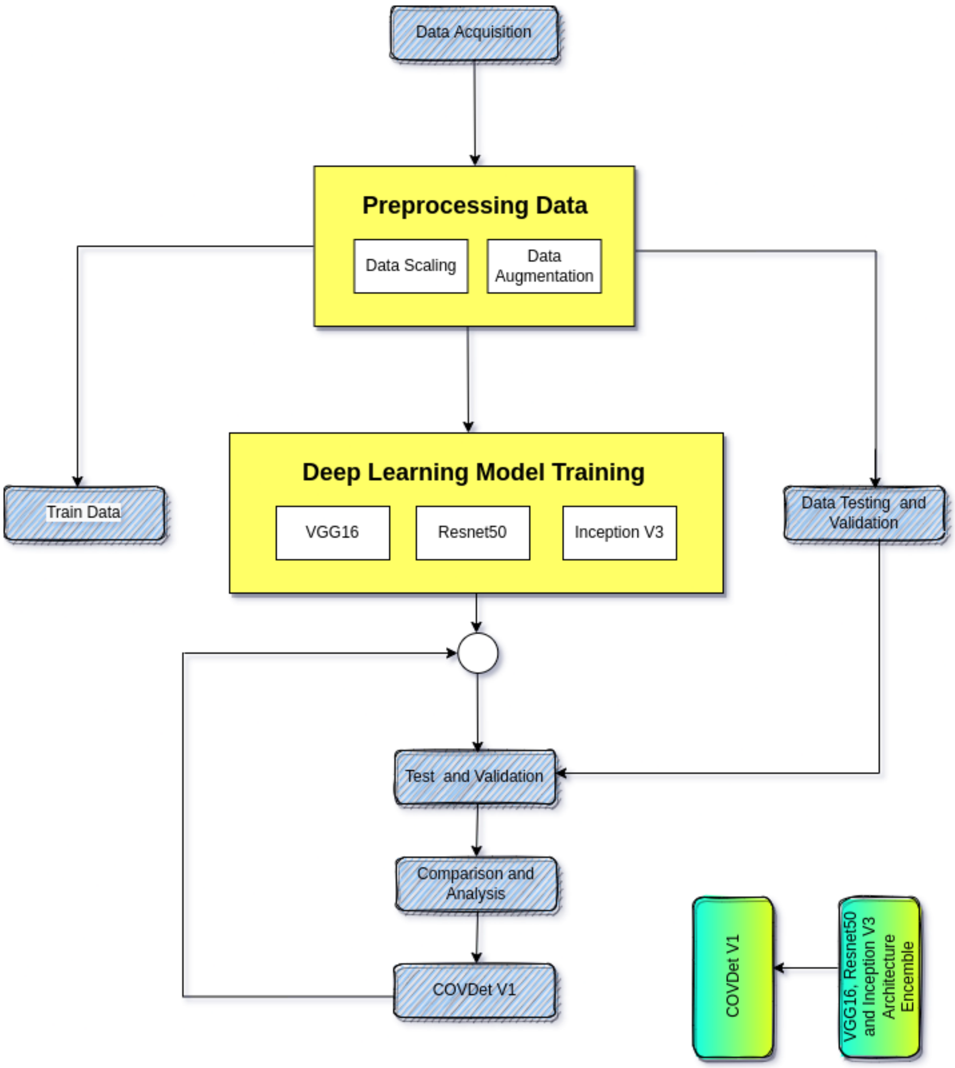

Figure 3.1: Workflow Diagram

Figure 3.1 provides a diagram of each process involved in the training and verification of our models. To get started, we've collected and processed data, including data scaling and augmentation. Next, we trained the dataset. For dataset training, we use three deep learning models which areVGG16, Inception V3 and ResNet50. The dataset was then checked and validated.. After that, we trained the data set using the COVDet V1 models we created, and then verified and validated the data for accuracy.

3.2 VGG

Visual Geometry Group, also known as VGG, is a first-rate Convolutional Neural Network(CNN) multiple layered architecture [6]. Ground-breaking object recognition models are based on the VGG architecture. It was primarily based on a study on how to increase the Neural Network and other similar networks' depth, Usually used for various detection and identification tasks. To make the characteristic feature extra non-linear, using the VGG 1 × 1 integration layer, without improving the acceptance field. Due to the moderate length of the convulsion filter, VGG may also contain excess weight; Clearly, extra dimensions equate to higher performance. Although this is not an unusual feature.

3.2.1 VGG16

VGG16, a convoluted neural network model, was created in 2014 and is still considered one of the best designs for image classification [6]. The VGG16 model is a successful image recognition method that utilizes a convolutional neural network as the core network.. It features a unique network structure that is easy to modify. The VGG16 network includes 33 filters and 22 maximum-pooling layers, with 16 layers made up of 5 blocks, each having its own maximum-pooling layer. ReLU's activation feature is applied between these layers. Next, there are three fully linked layers that hold most of the parameters of the network. Finally, the probabilities of each classification of pulmonary symptoms are calculated using a Softmax activation feature. A 224 × 224 × 3 RGB image is used as the network input with a 3 × 3 size kernel; this image has been moved through numerous evolutionary layers. The filters are connected to two parts between the maximum-pooling layers and are measured in 2 × 2 measurements.

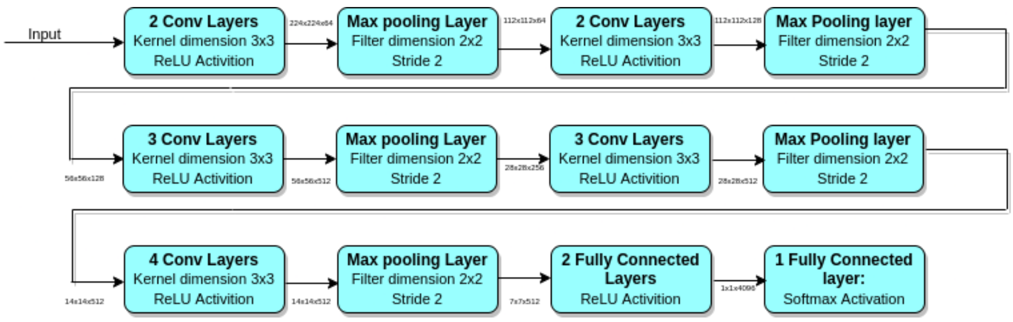

Figure 3.2: VGG16's Detail Architectture

3.3 ResNet

The Residual Network, or Resnet, is a well-known deep learning model, first developed in [6]. Based on known elements from the pyramidal cells of the cortex, it is without a doubt one of the most widely used and efficient models of deep learning. With its extremely deep network, ResNet, which acts as an ensemble of smaller networks, is particularly effective in dealing with problems such as the disappearance of gradients. ResNet's key feature is its own ability to train deep neural networks with over 150 layers.

3.3.1 ResNet50

ResNet50, a fifty-layer CNN, helps in the training of extremely deep neural networks by avoiding difficulties with invisible gradients. The ResNet50 model is substantially smaller due to the usage of a global average pool rather than a fully connected level, which decreases the model's size to 102 megabytes [9]. Residual block learning is a unique feature of ResNet. This model introduces the idea of avoiding the first connection. A single layer's output can be routed to a remote layer in addition to the immediate layer in such a model. This means that each level should be 2-3 hops away from the level directly below. This model has five stages, each with its own set of convolution layer configurations.

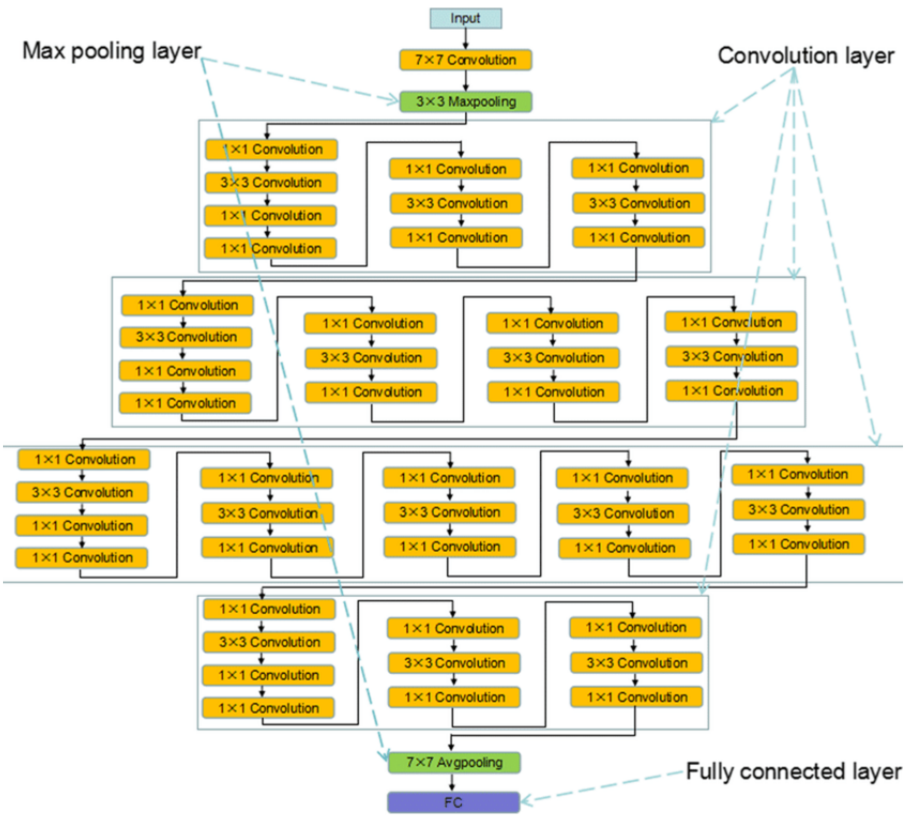

Figure 3.3: ResNet50's Internal Arcchitecture

3.4 Inception

A convoluted layer with 64 filters and a kernel size of 7 $\times$ 7. A maximum pooling layer with two stride sizes follows. Then there's a convoluted layer with 64 filters and a 1 $\times$ 1 kernel size, followed by a 3 $\times$ 3 kernel size filter with 64 filters. Following that is a convoluted layer with 256 filters and a 1 $\times$ 1 kernel size. These three levels are reproduced three times in this phase, for a total of nine layers. There are three evolutionary layers: 128 filters with a 1 $\times$ 1 kernel size, 128 filters with a 3 $\times$ 3 kernel size, and 512 filters with a 1 $\times$ 1 kernel size. In this phase, these three levels are duplicated three times, for a total of nine layers. Then there are three evolutionary layers with 128 filters and a 1 $\times$ 1 kernel size, 128 filters and a 3 $\times$ 3 kernel size, and 512 filters and a 1 $\times$ 1 kernel size. These layers have been repeated four times, resulting in a total of 12 layers. Next, we have 256 filters and a 1 $\times$ 1 kernel size convoluted layer, as well as two further convoluted layers with 256, 1024 filters and 3 $\times$ 3, 1 $\times$ 1 kernel size. It is then performed six more times. There are a total of 18 levels. Then there's a complicated layer with 512 filters and a 1 $\times$ 1 kernel size, then 512, 2048, and 1 $\times$ 1, 3 $\times$ 3 kernel sizes. For a total of nine levels, this is repeated three times. Finally, we utilize average pooling to generate a fully connected layer that has 1000 nodes before reducing the number of layers with the Softmax function.

The Convolutional Neural Network leverages inception to provide more efficient computation and deeper networks by decreasing dimensionality via stacked 11 convolutions. The modules were created to address difficulties such as computational expense, such as the framework's need for less RAM, and overfitting, among others [7]. In other words, instead of stacking many kernel filter sizes sequentially within the CNN, the approach organizes them such that they all operate at the same time. Convolution is conducted on an input utilizing not one, but three distinct sizes of filters(1x1, 3x3, 5x5) in the most basic version of an inception module. [7]. Furthermore, maximum pooling is employed. After that, the outputs are combined and transferred to the next layer. By designing the CNN to complete its convolutions on the same level, the network grows in breadth rather than depth.

3.4.1 Inception V3

Inception V3 intends to enhance the usage of computing resources within the CNN network by increasing the depth and breadth of the network by stabilizing computation processes [9]. Network designers invented the term "inception module" to describe an efficient network architecture that may be used as a building element to avoid connections. The first module's purpose is to operate as a "multi-level feature extractor" by computing 1 $\times$ 1, 3 $\times$ 3, and 5 $\times$ 5 convolutions simultaneously in the same network module[9]. The output and channel size of these filters are then reset to the next level. This inception module is occasionally replicated geographically by stacking with the highest-pooling layers to lower dimensions to a functional level for computing.

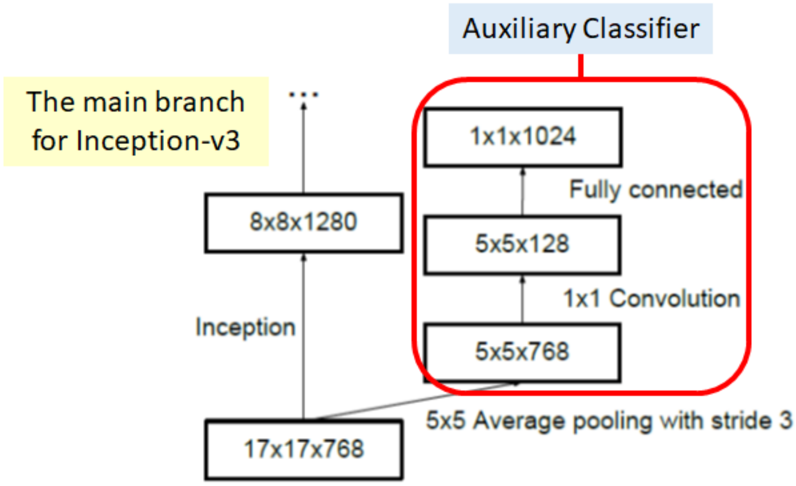

Figure 3.4: Architecture of Inception V3

3.5 Convolutional layer

The fundamental element of a convoluted neural network is a convoluted layer. It contains a collection of filters (or kernels) whose parameters must be learned during training. Filters are often smaller in size than real images. Each filter creates an activation map by combining it with the image. The filter is slid over the image's height and width for rotation, and the dot product between each component and the filter's input is computed at each spatial location.. The initial entry in the activation map is calculated by tying the filter to the green(figure) component of the input image. This technique is repeated for each element of the input image to create an activation map. The activation maps of each filter are stacked along the depth level to create the output volume of the convoluted layer. Each element of the activation map can be considered as the output of a neuron. As a result, each neuron input is connected to a small spatial region in the image, the size of which is equal to the size of the filter. The parameters of all neurons are shared on an activation map. The network is pushed into trained filters that respond the most to a specific region of the input due to the local connection of the convoluted layer. The lower-level properties of images are captured by the first transformational layers, while the higher-level properties are extracted by subsequent.

3.5.1 Activation function

The net inputs, which are processed and turned into an output result known as a unit activation result using an activation function, are the most important units in the construction of a neural network[11]. A network layer's output values might be somewhere between $\infty and \infty$.

3.6 Rectified Linear Unit (ReLU)

In neural networks, ReLU is a non-linear activation function that is commonly utilized [8]. Because not all neurons are stimulated at the same time, ReLU is more efficient than other functions. The weights and biases are not updated during the back-propagation stage in neural network training in some circumstances because the gradient value is zero.

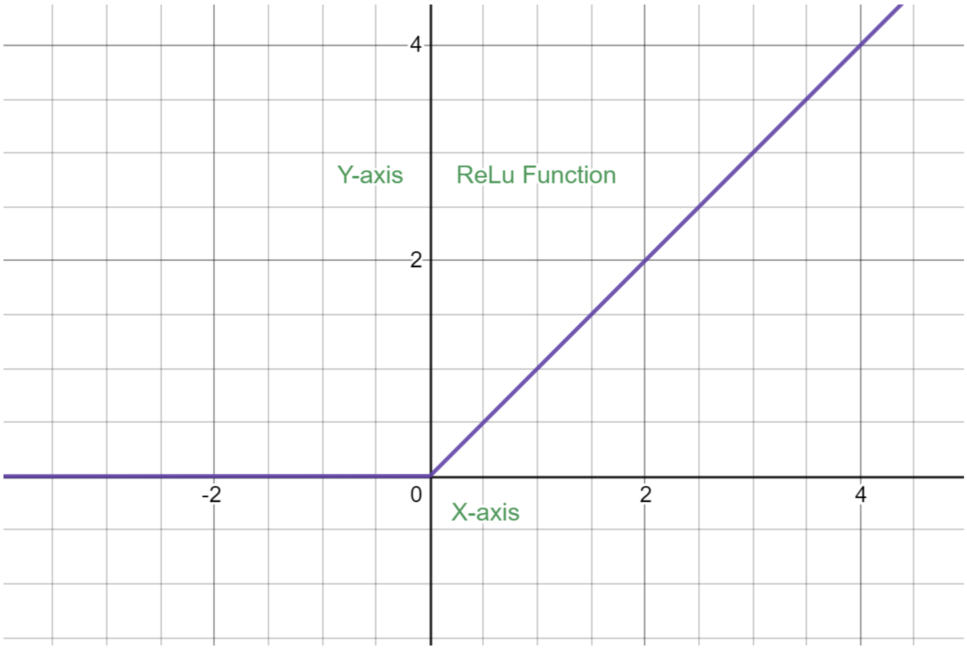

Figure 3.5: ReLU Function of Plotted Graph

3.7 Max Pooling Layer:

The max pooling layer identifies and chooses the maximum elements, which means it selects the brightest pixels in any picture from the region of the feature map covered by the filter. A feature map contains the brightest pixels from the preceding map or picture after the max-pooling layer procedure. The max-pooling layer decreases the size of an input representation, such as an image or a hidden-layer output matrix, by down sampling it. This enables assumptions to be made about how features in sub-regions should be binned. A max-pooling layer, which works by applying a maximum filter to non-overlapping sub regions of the original representation, can be used to darken an image's backdrop while lightening the image's pixels.

3.8 Optimizer: Adam

Adam is a type of optimization method which can be used to make changes to a system with weight values depending on the testing phase rather than the traditional stochastic gradient descent procedure [35] . This method's Implementation is simple, effective in terms of computation and no need for many memory requirements [32]. The gradients are resistant to diagonal re scaling.The method can also be used to resolve issues with non-stationary targets and/or extremely noisy and/or less gradients [32]. Each network weight has its own learning algorithm, which is adjusted as learning progresses. There are two combining the advantages of Adam. Adaptive Gradient Algorithm (AdaGrad) mainly enhances performance on situations with thin gradients by maintaining a per- parameter learning algorithm. Root Mean

Square Propagation (RMSProp) additionally keeps per-parameter training data that are adjusted by calculating the average of current gradient orders of magnitude for the weights.Some parameters are also used. Alpha is the Step size or learning rate. Beta1 estimates of the first moment's exponential decay rate. Beta2 estimates of the second moment's exponential decline rate. Epsilon avoids any division by 0 and this is a small number. Adam mainly achieves good results but firstly.

3.9 plotGraph()

This method creates a DataFrame from the given history of a model, and later plots it into a graph. A DataFrame is a completely heterogeneous two-dimensional, size-mutable tabular data set. The method has one parameter 'h' which takes a history generated from the fit_generator of a model. After creating the DataFrame with a figure size of (8, 5), it plots a graph with grids being shown.

3.10 print_layer_trainable()

This method prints each layer information from the convolutional model. For each layer in the convolutional model, it prints the layer name and if it's trainable or not.

3.11 trainableLayers()

This method returns each layer name from the convolutional model. The method has one parameter 'model' which takes the passed model. Then, the method loops through this model's layers and saves them into a list. Lastly, the created list is returned.

3.12 transferLayer():

This method creates a new model from the given model and layers, and later returns it after enhancing it. The method has two parameters 'model' and 'layer' which takes the passed model and it's trainable layers. Initially this method starts a new Keras sequential model. Then it adds the convolutional part of the model from above. After that, it flattens the output of the model because it is from a convolutional layer. Later, it adds a dense or fully-connected layer. This is for combining features that the model has recognized in the image. Finally, adds the final layer for the actual classification and returns the new model.

3.13 Ensemble Modeling

Ensembles are predictive multi layer method models that aggregate predictions from two or more different models to create a single forecast [20]. The ensemble participants' predictions can be aggregated using statistics like the mode, mean, or more advanced approaches that determine the amount and in what circumstances to consider individual participants. Ensembles have been used to improve the forecasting performance of an individual forecasting model on a predictive modeling task. This is accomplished by adding bias to the system, which reduces the variance element of the prediction error. [20][4] . Another important advantage of ensemble methods is bigger robustness or consistency in an architecture's standard results. The efficiency of a model's bias and variance are linked. Bias and variance are mainly errors from a model. Increasing the variance can sometimes be a simple way to reduce bias. Increasing the bias is a simple way to reduce variance. The fundamental advantage of employing ensembles is to increase predictive efficiency by decreasing the variance characteristics of forecast mistakes. We considered some factors like, Noise, variance and bias, explainability and simplicity, generalizations, inference time [4] Bagging, Boosting, Stacking, Blending are some techniques for ensemble modeling. Bootstrapping, Random Forest, Extra-Trees Ensemble are done in Bagging method. Adaptive Boosting and Gradient Boosting is done in the Boosting method. When we find a problem we can classify it or do regression to solve it. To predict a result we can do Max Voting, Averaging or Weighted Average[4].

3.13.1 Performing Layers

We have used VGG16, ResNet50 and Inception v3 these three architectures and named it COVDet19 v1. The result probability from different designs with the

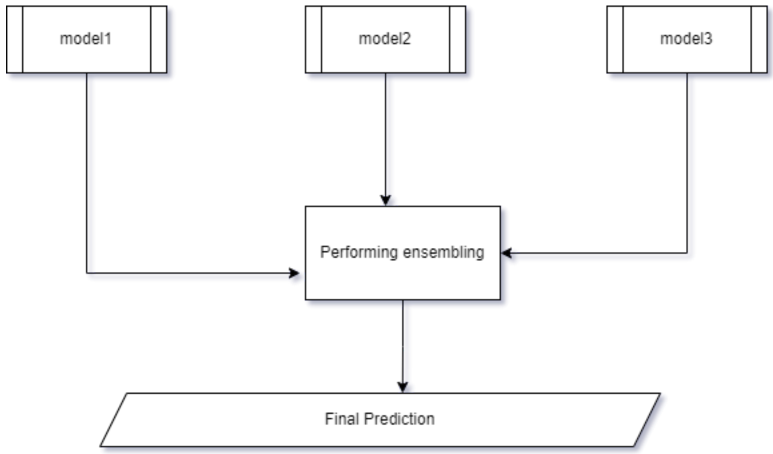

Figure 3.6: Structure of Ensemble Modeling.

same output dimension will be used as input in the ensembling layer. It will determine the prediction likelihood for two terms: COVID positive, COVID negative by ensembling the numerous probabilities [36]. This is how ensemble modeling is performed to predict a simple and less cost result and error.

3.13.2 Output Layer

In this layer we predict the result. 1 COVID positive, 2. COVID negative . While using COVDet19 v1 model predicted final result probability.
If our predicted final result probability's first predicted index is lesser than the second predicted index then the output will give a result with COVID positive. As well as if our second predicted index is lesser than the first predicted index then the output layer will give a result with COVID negative. This is how the output layer works and gives the whole result which is error-free and less costly.

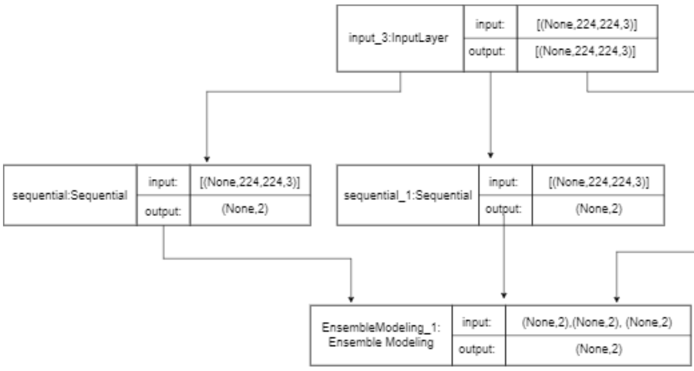

Figure 3.7: Output Layer of Ensemble Modeling using COVDet19 v1 model

Chapter 4

Implementation

4.1 Dataset

Source:
COVID-19 Radiography Dataset: Constructed here.

Data Sample

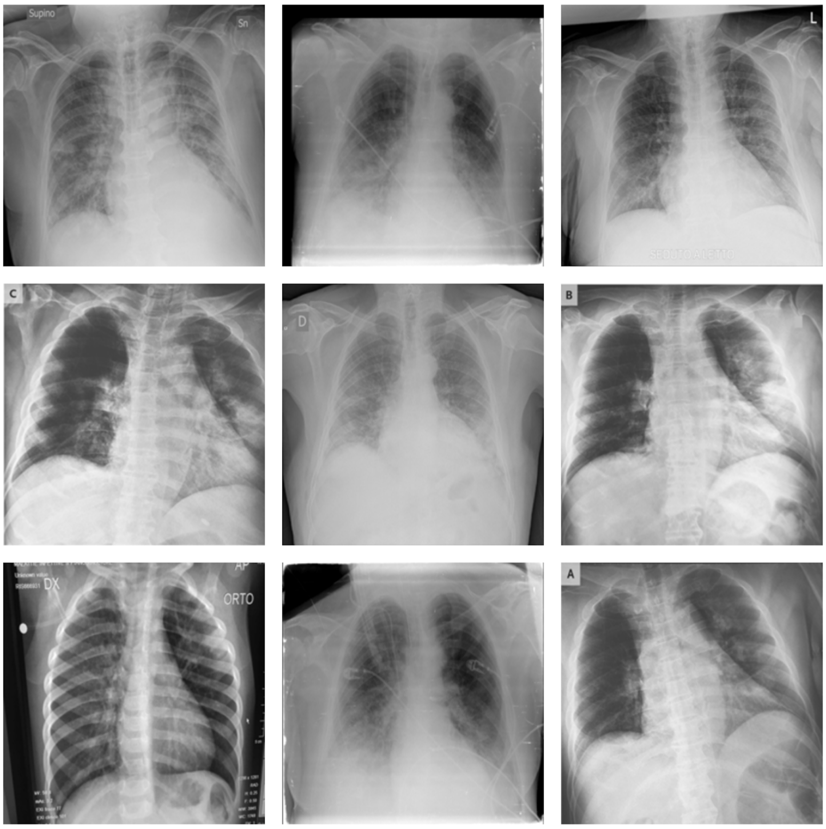

Figure 4.1: Dataset Sample images

Data Classification

Classification is the process of categorizing a set of data into one of several categories.Target, label, and categories are all terms used to describe the classes. For COVID-19 frontal-view chest X-Ray images, we use the COVID chest x-ray dataset[44]. We divided the dataset into 7:2:1 where we chose 70% images of our dataset as a Train set, 20% was used as a test set and 10% were kept as a validation set. Dataset splitting table is given belowcitetrung-2019-

	Normal	Covid-19	Total
Train	134	2531	9665
Test	2037	730	2767
Validation	1019	353	1372

Training Set

The goal of the training dataset is to use a machine learning model to uncover the predictive relationship. It is the stage in which the machine learning algorithm process is fed labeled example data with answers or output labels[41].We are actually developing the model by training it. If we do not train our dataset our machine learner will never learn the behavior of the data and all the hyperparameters finding the right kind of a model with the right tuning of the hyperparameters that this is the one that can serve the purpose right.

Testing Set

Once the model is complete, we utilize the Test dataset to determine the accuracy of the hypothesis on the model's performance. The test data set is a set of data used to provide an objective assessment of a final model fit on the training data set. In some cases, the algorithm may learn particular properties of the training set as it iterates to improve performance, using a series of examples for real-world study. Better results will create trust in the model's ability.

Validation Set

The validation set refers to comparing the results of models with various parameters and selecting the best model for the validation set. While setting the model's hyper parameters, the validation data set provides an unbiased evaluation of a model fit on the training data set[44]. The fitted model is used to predict the responses for the observations in a second data set called the Validation data-set [37][2][1]

4.2 Image resizing

The proposed model intends to diagnose COVID 19 from chest X-ray (images) focused on the lungs and surroundings. Prior to the training session, the image in the dataset is downscaled to a lower resolution (224 x 224) to increase the predictive

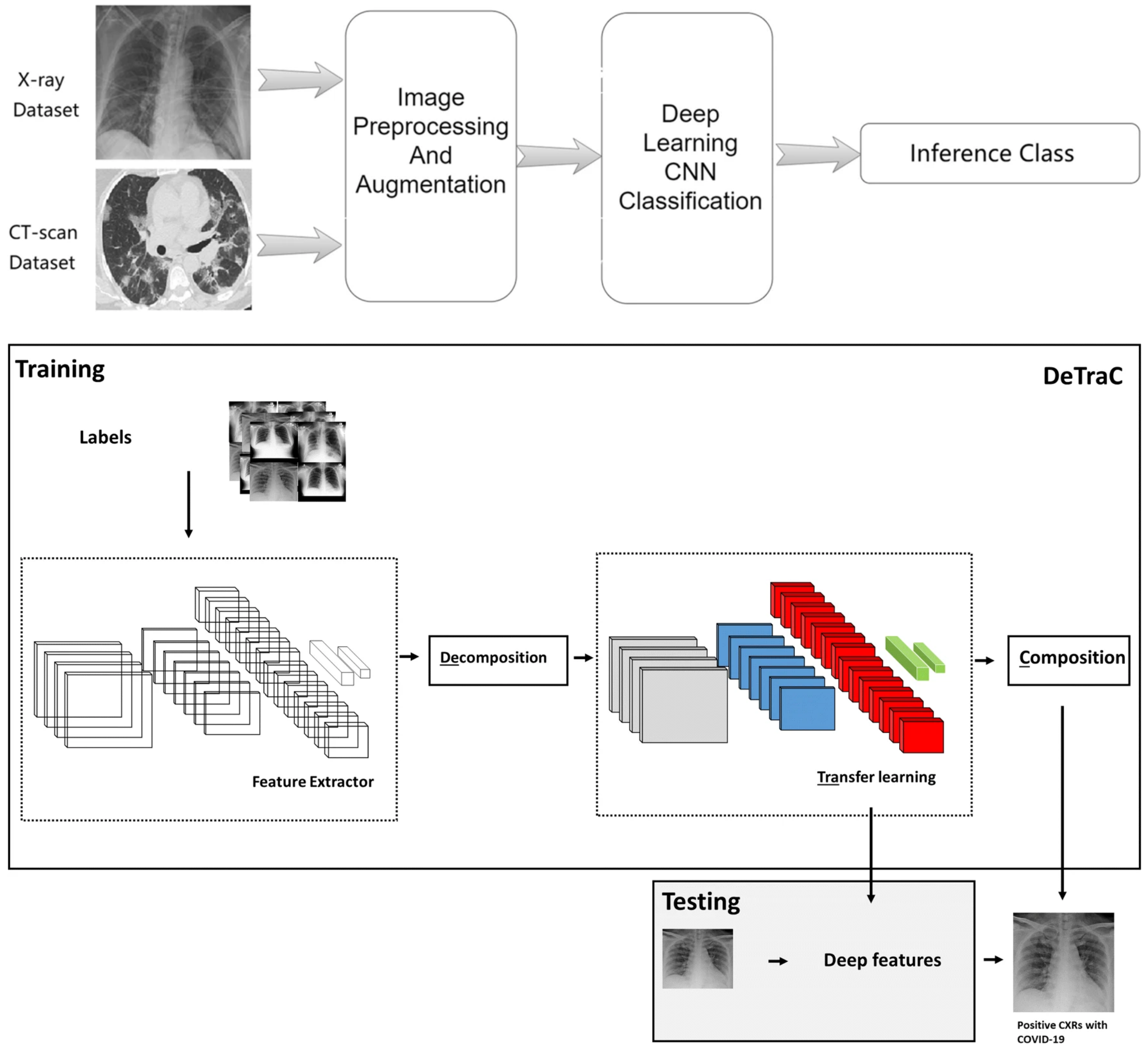

Figure 4.2: Data testing

power of the model, increasing the performance[47]. Resizing to a lower dimension and creating mini-batches of input image bypasses the computational limitation of image processing[3]'tf.Keras.preprocessing.image.ImageDataGenerator' class changes the resolution of images into target size, shape, pixel counts, etc [45].

4.3 Normalization and scaling

Normalization is a procedure to scale data into percentages (divide by 255), which converts it to a range of 0-1. For normalization, Principal Component Analysis (PCA) is a data table analyzing technique in which the data table is described by several inter correlated quantitative dependent variables [10]. Post co-variant matrix is symmetric and semi definite and will have orthogonal eigenvectors[5]. The ImageDataGenerator class of keras would be used for this normalization process. Hence, the parameters (in-built) would take care of the scaling.

4.4 Architecture Training

We partitioned our dataset into three portions to train neural networks, as we need to find the proper weights for the neural connection. Neural Network Topology can be seen as the relationship between them by means of their connection.VGG16, ResNet50, Inception V3 were used by our model COVDet19 v1. When we implemented these neural network topologies, the epoch was 40 and the batch size was 16. On our system, we ran this dataset with the following configuration settings: CPU: Intel Core i5 8500, RAM: 16GB, and GPU: NVIDIA GTX1070Ti 8GB.

Chapter 5

Result Analysis

5.1 Training and Validation Information for Individual Models

VGG16:

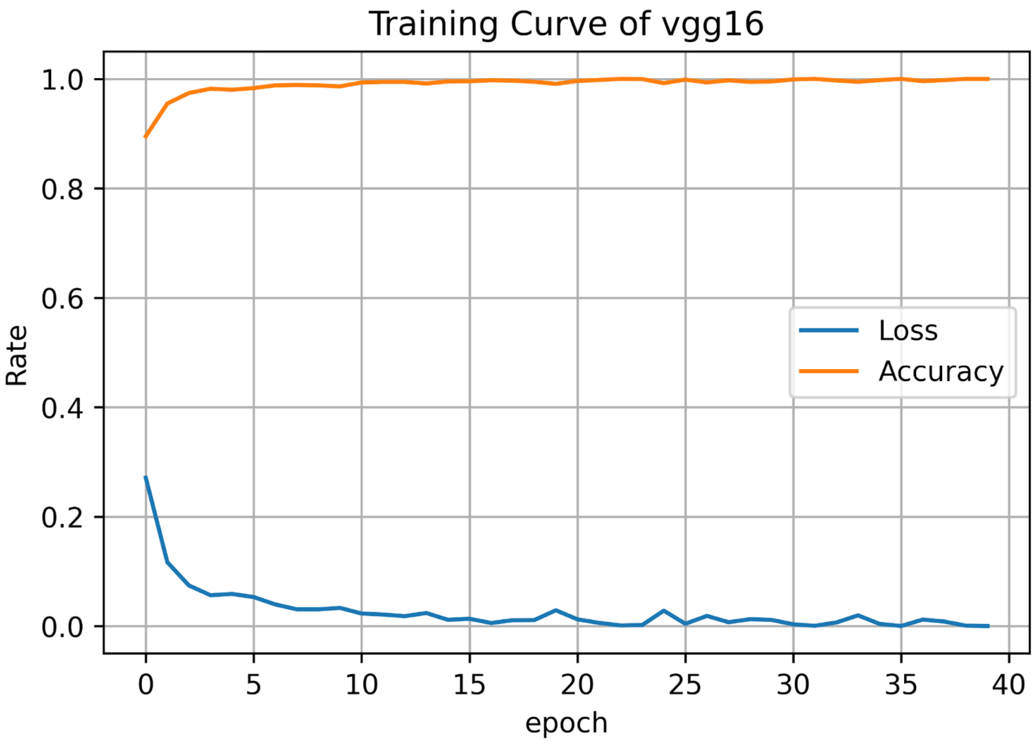

Figure 5.1: Training curve of VGG16.

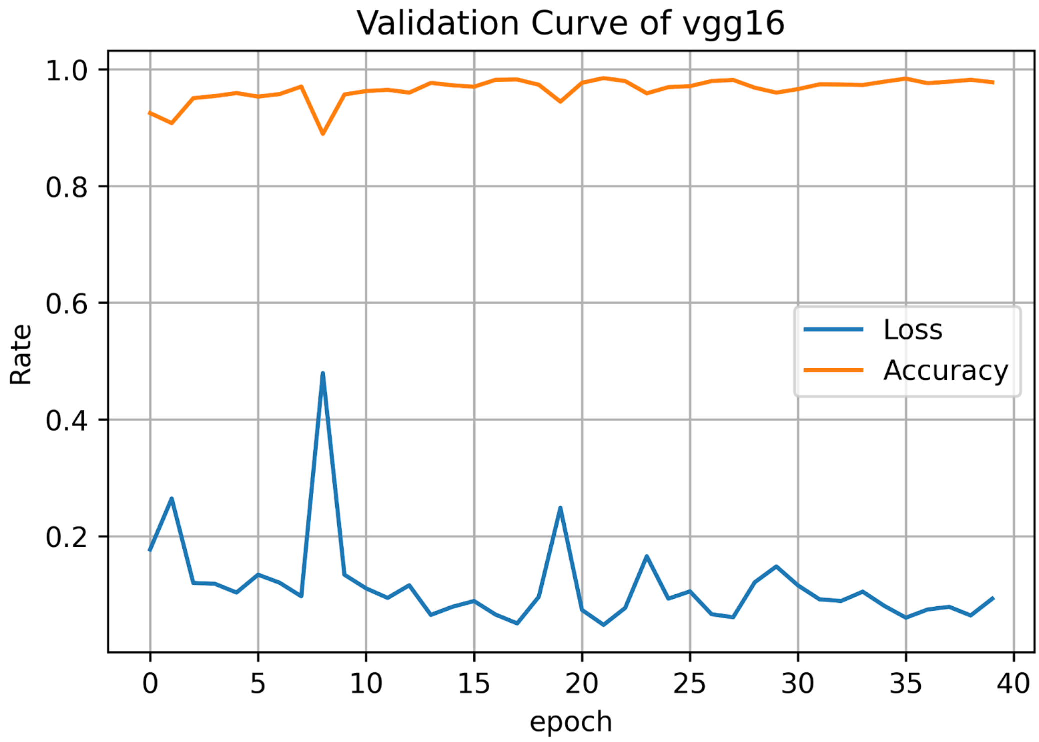

Figure 5.2: Validation curve of VGG16.

ResNet50:

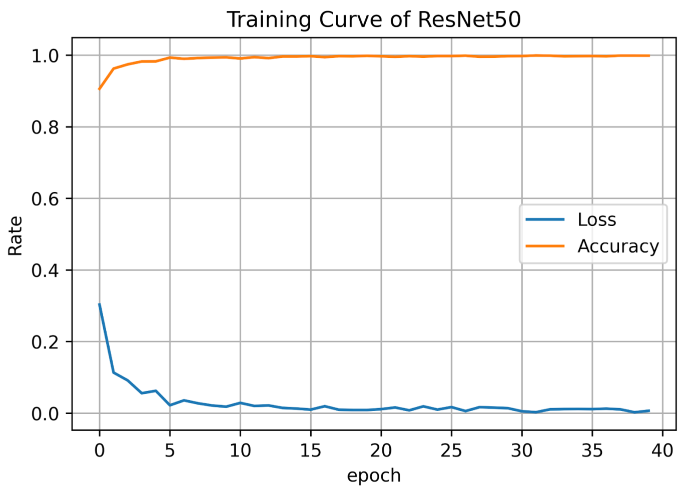

Figure 5.3: Training curve of ResNet50.

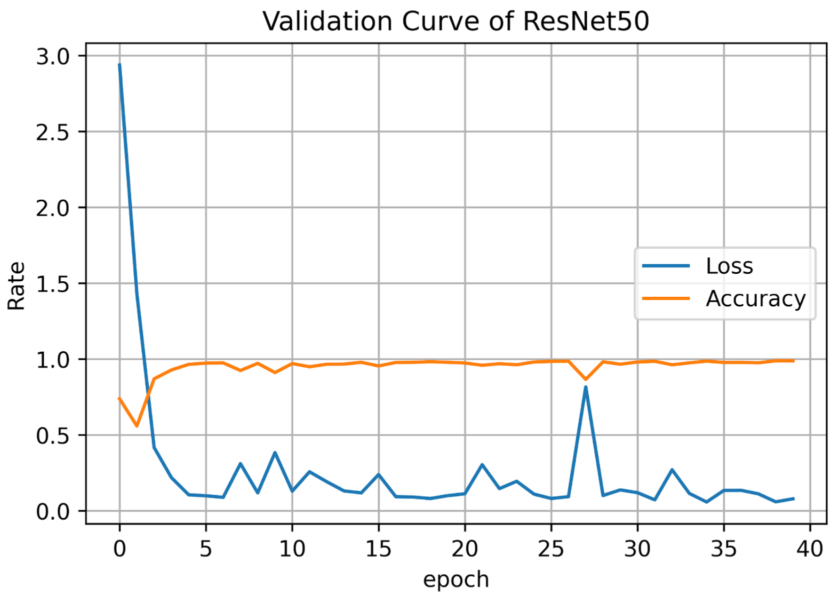

Figure 5.4: Validation curve of ResNet50.

Inception V3:

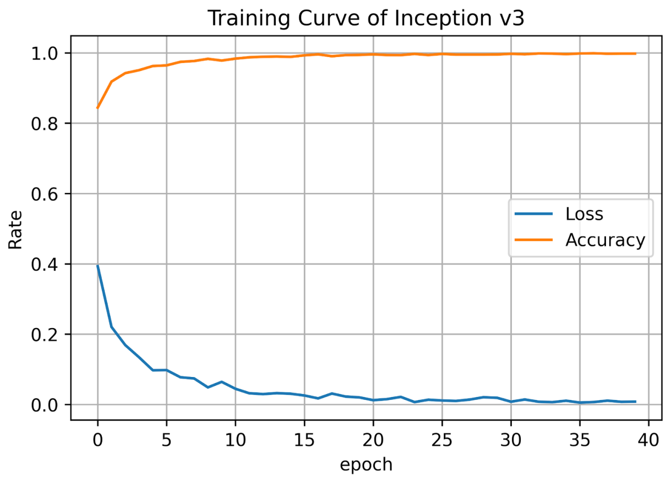

Figure 5.5: Training curve of Inception V3.

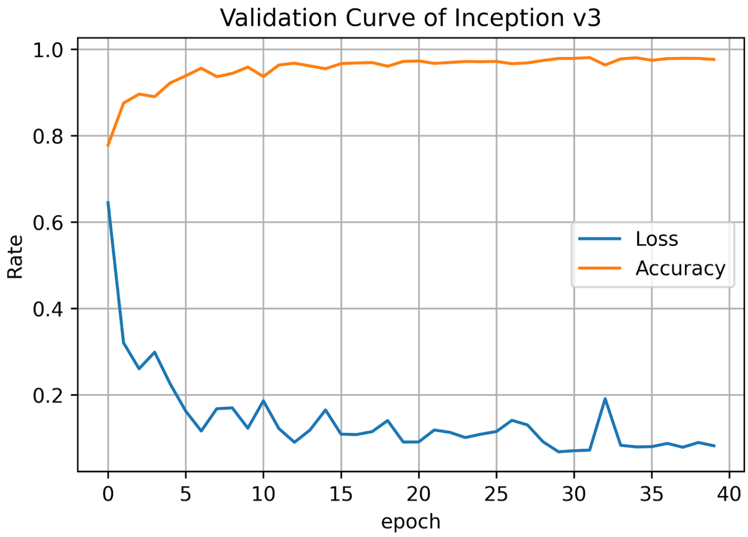

Figure 5.6: Validation curve of Inception V3.

Architecture	val_categorical_accuracy	val_loss
VGG16	97.82%	0.0794
ResNet50	98.89%	0.0619
Inception V3	97.65%	0.0821

Table 5.1: Comparing our used models

Figure 5.7: Comparing our used models graphically.

From the categorical accuracy of Table 1, we can determine that VGG16, ResNet50 shows us 97.82%, 98.89% and 97.65%.

Confusion Matrix for Individual Models: VGG16:
In the figure below, you can see, among the 4136 photos, the model successfully classified 3041 photos as COVID19 positive, and 1004 photos were classified as COVID19 negative. Though, the model also gave 13 false positives and 78 false negatives.

	precision	recall	f1-score	support
Normal	0.9750	0.9957	0.9853	3054
Affected	0.9872	0.9279	0.9566	1082
accuracy			0.9780	4136
macro avg	0.9811	0.9618	0.9710	4136
weighted avg	0.9782	0.9780	0.9778	4136

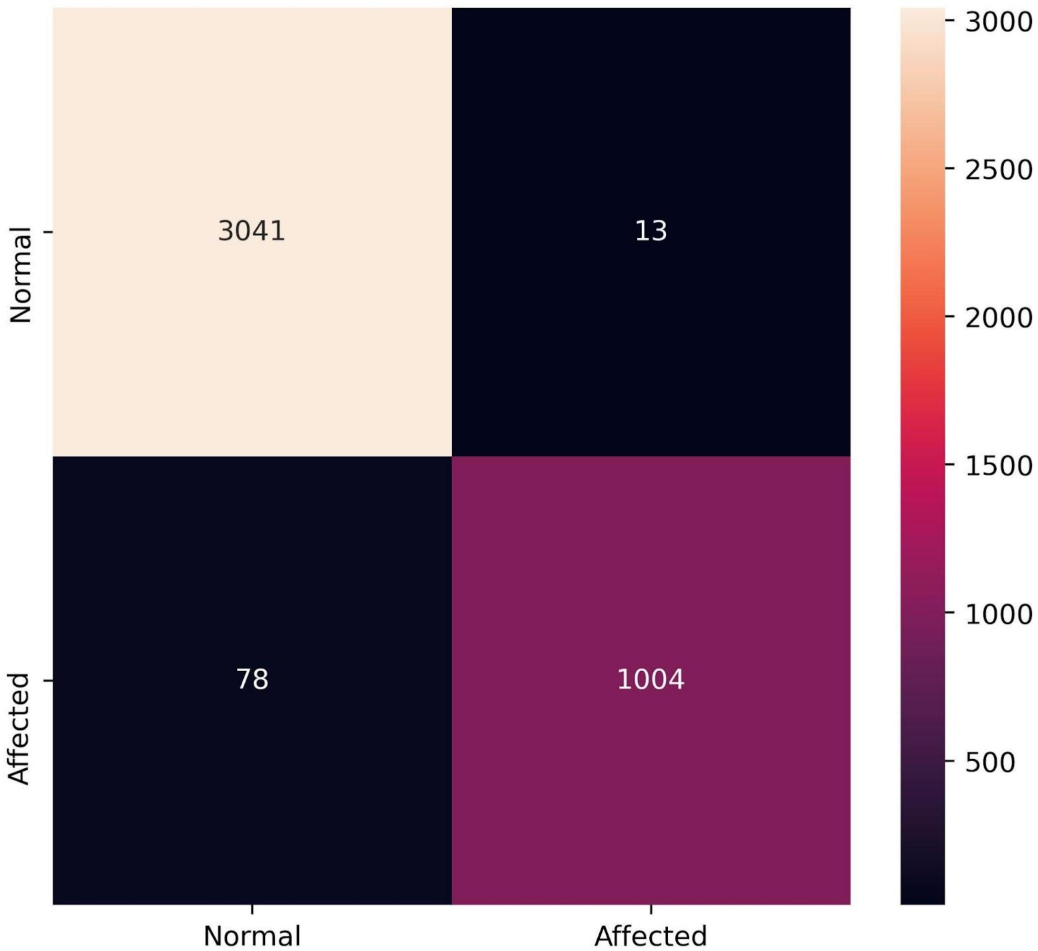

Figure 5.8: Confusion matrix for VGG16.

ResNet50:

In the figure below, you can see, among the 4136 photos, the model successfully classified 3043 photos as COVID19 positive, and 1047 photos were classified as COVID19 negative. Though, the model also gave 11 false positives and 35 false negatives. So the model clearly performed better than VGG16.

	precision	recall	f1-score	support
Normal	0.9886	0.9964	0.9925	3054
Affected	0.9896	0.9677	0.9785	1082
accuracy			0.9889	4136
macro avg	0.9891	0.9820	0.9855	4136
weighted avg	0.9889	0.9889	0.9888	4136

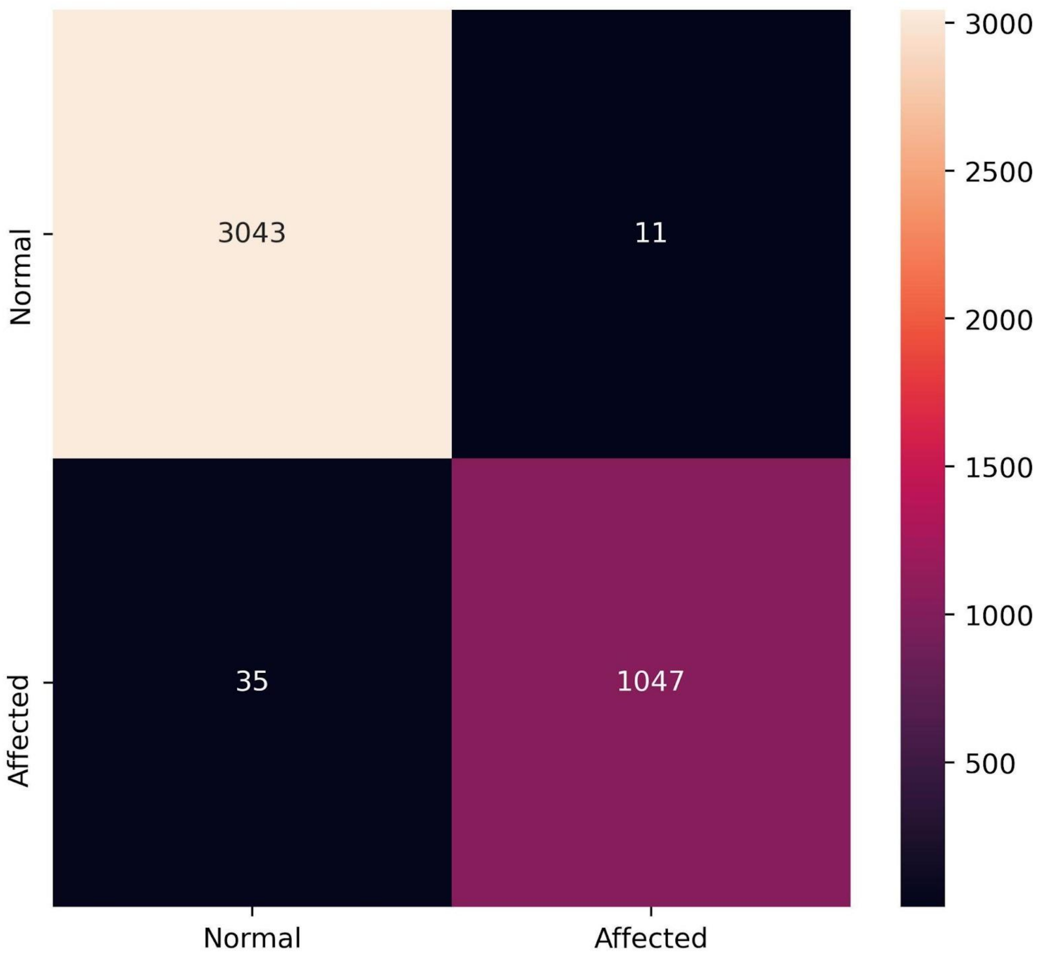

Figure 5.9: Confusion matrix for Resnet50.

Inception V3:

In the figure below, you can see, among the 4136 photos, the model successfully classified 3011 photos as COVID19 positive, and 1028 photos were classified as COVID19 negative. Though, the model also gave 43 false positives and 54 false negatives. So the model clearly performed better than VGG16 but worse than ResNet50.

	precision	recall	f1-score	support
Normal	0.9824	0.9859	0.9841	3054
Affected	0.9599	0.9501	0.9549	1082
accuracy			0.9765	4136
macro avg	0.9711	0.9680	0.9695	4136
weighted avg	0.9765	0.9765	0.9765	4136

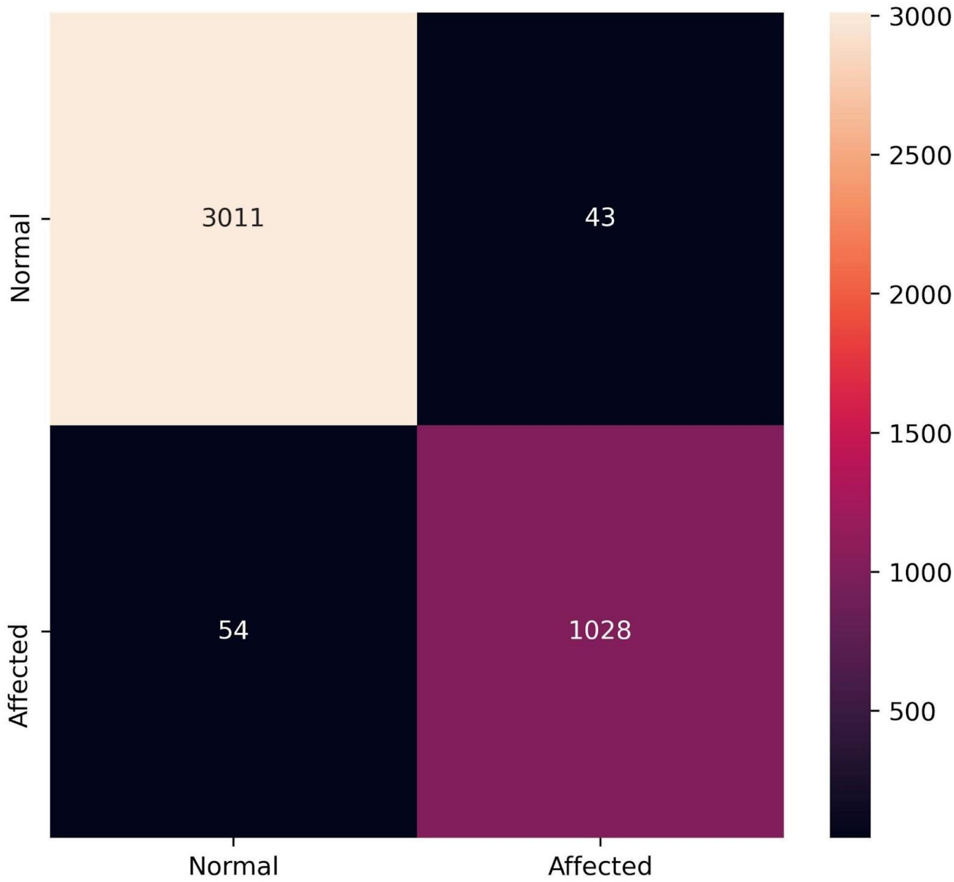

Figure 5.10: Confusion matrix for Inception V3.

Ensemble Modeling (COVDet19 v1):

In our COVDet19 v1 model, we used ensemble modeling on VGG16, Inception V3 and ResNet50. From the training and validation curves of COVDet19 v1 we

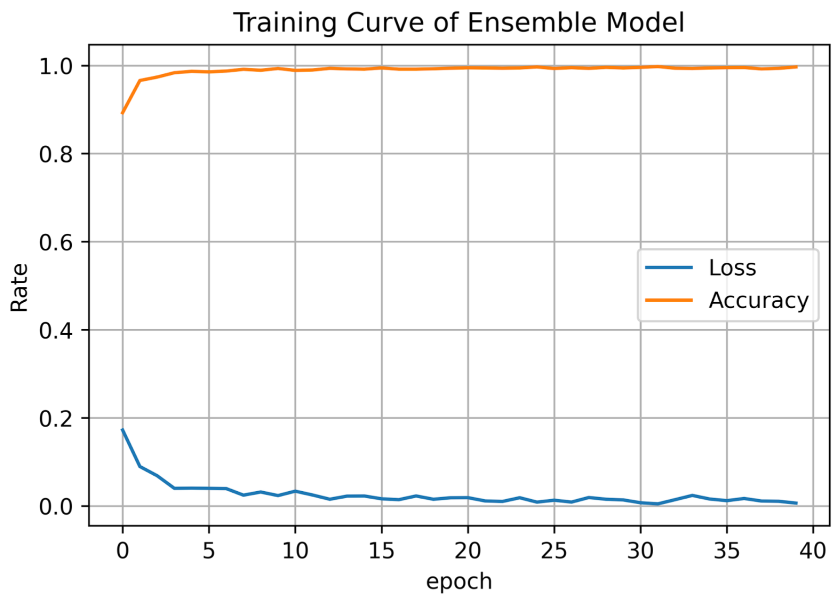

Figure 5.11: Training curve of COVDet19 v1

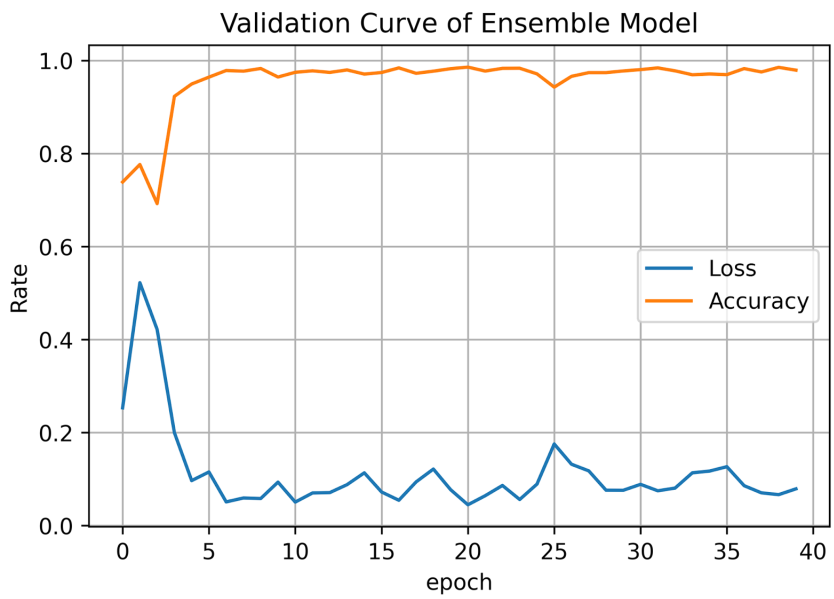

Figure 5.12: Training curve of COVDet19 v1

can see that we have achieved 97.92% validation accuracy.

	precision	recall	f1-score	support
Normal	0.9898	0.9820	0.9859	3054
Affected	0.9503	0.9713	0.9607	1082
accuracy			0.9792	4136
macro avg	0.9700	0.9767	0.9733	4136
weighted avg	0.9794	0.9792	0.9793	4136

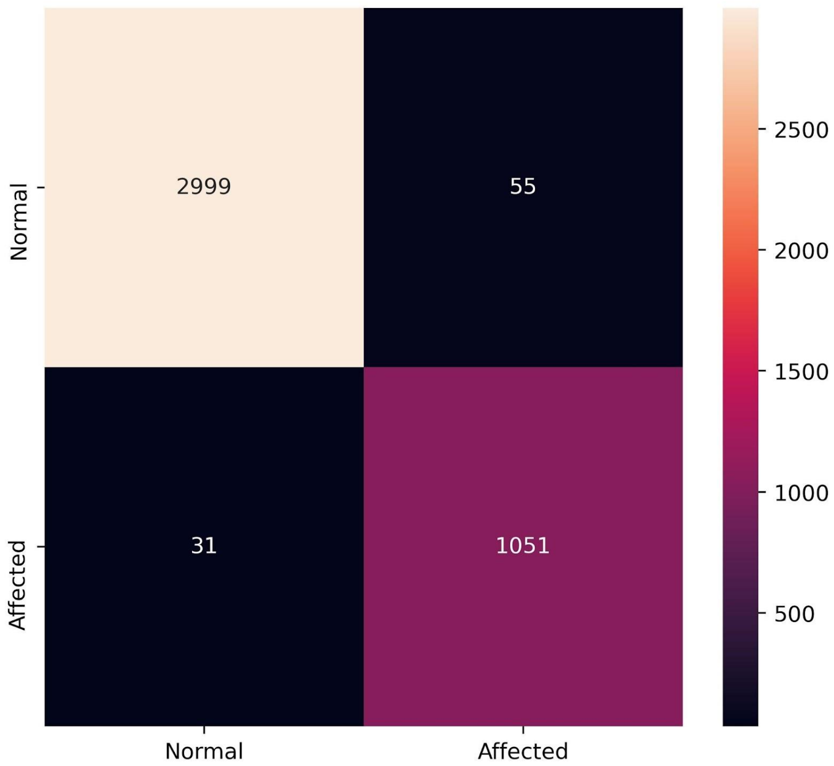

Figure 5.13: Confusion matrix of COVDet19 v1

Confusion Matrix for COVDet19 v1:

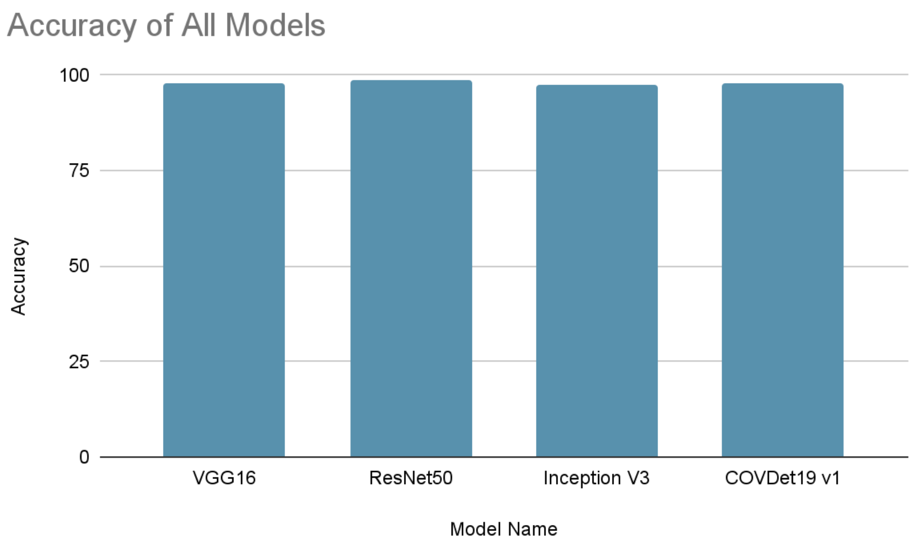

Figure 5.14: Comparing our used models with our custom COVDet19 v1 model graphically.

Comparison with the Architectures Used:

COVDet v1 achieves a greater accuracy (97.92%) than VGG16 and Inception V3 with lesser value loss (0.0604). Therefore, this is the model that we're going to use in our future work.

Chapter 6

Conclusion and Future Work

6.1 Conclusion and Future Work

It's been over two years, and the COVID-19 epidemic is still going strong. Rather, the situation is getting worse day by the day. COVID-19 viral varieties continue to emerge. COVID-19 testing is becoming more popular, with more people visiting hospitals and clinics every day. The results take almost a full day or a half day to produce. Patients who are significantly afflicted by COVID-19 may find it more difficult to withstand the agony since results take a long time to come back. Furthermore, clinicians cannot treat patients if they do not know the results, as incorrect COVID-19 medication might be fatal for some individuals. The longer time passes, the worse things will get for the sick. It may even cost them their lives. To prevent the virus from spreading further, early identification and treatment of COVID-19 are critical.

Our model will be able to identify COVID-19 by evaluating the X-ray pictures of patients, as well as categorize the intensity of COVID-19, in order to ameliorate the circumstances of patients. We used the dataset to train VGG16, ResNet50, and InceptionV3 models, and compared the results to our own COVDetV1 model, which will be able to finish COVID-19's binary classification in the shortest amount of time. Furthermore, our model for identifying COVID-19 has a 97.92 percent accuracy rate. Because our model has a good overall performance, we feel it can assist doctors and health specialists in making clinical judgments.

In our future work we'll try to add two or more models and combine them and will analyze if we can figure out a bigger accuracy rate. Also while doing our research the whole pandemic was a limitation for collecting datasets. We'll try to do our research in more diseases like pneumonia, lung cancer etc. and compare the findings more properly. Furthermore, we'll study furthermore to collect more datasets.

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