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Infection Severity Detection of CoVID19 from X-Rays and CT Scans Using Artificial Intelligence

Nimai Chand Das Adhikari*

Senior Data Scientist, EDS, Robert Bosch Engineering and Business Solutions Private Limited, 123 Industrial Layout, Hosur Road, Koramangala, Bangalore – 560095, India

Email: dasadhikari.nimaichand@gmail.com

Abstract

December 2019, marked with a widespread infection due to a new matured member of SARs Virus named as SARS-CoV2 (Novel Corona Virus-2019) infecting more than 20 lakhs people across the globe. This effect made the World Health Organization to declare COVID-19 (Corona Virus Disease, 2019) as a pandemic situation and called a worldwide lockdown to dampen and flatten the infectious curve and diminish the infection growth. With Limited number of COVID-19 test kits in hospitals and the increasing daily cases has asked for an immediate measure for the development towards the Automatic COVID-19 Detection and Alternative Diagnosis Systems (ACD-ADS). This research presents a two-staged DenseNet architecture to diagnose the COVID19 infections from X-rays and CT-scans images to decrease the turnaround time of the doctors and check more patients during that point of time. This research work talks about the end to end solution for the diagnosis to extract and mark the most infectious regions on the imaging pictures to help the doctors and medical practitioners in this pandemic situation. The system achieved an accuracy of 99% and specificity of 94.1% using the DenseNet network on the X-rays images and an accuracy of 87% and specificity of 86.5% for the CT Scans in the Validation Sets. In a sample of 22 images for the CT-Scans of the reported patients having the COVID-19 infections in a real-time analysis, the model performed with detecting correctly for all the 22 patients. Any model can never replace a doctor nor can decide like a doctor who takes many other factors into the account that impacts a decision at a particular point of time. Hence, I propose a network called Automatic Diagnostic Medical Analysis for the COVID-19 Detection System (ADMCDS) that takes the images and tries to find the infectious regions to help the doctor better identifying the diseased part if any.

Keywords: Pre-Trained Architectures; VGG; ResNet50V2; InceptionResNetV2; DenseNet; Xception; MobileNet; NASNet; COVID19; SARS-CoV2; Neural Networks; Computer Vision; Pandemic.

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* Corresponding author.

1. Introduction

In December 2019, Wuhan in China and its near provinces saw the detection of a new kind of virus named as Severe Acute Respiratory Syndrome coronavirus 2 which is also called as SARS-CoV2 [1] that caused severe infections among the people in the near provinces within a very short period. The number hence spread to the whole world and is still in the growing curve/pattern day by day. This emergence of the new kind of viral attack has caused and raised serious concerns all over the world as a threat to the health of the public [2]. This has caused a pandemic situation across the globe. Before this there were only 6 types of Corona Virus reporting's that could highly infect human beings [3,4]. Some of the details involve infections towards the upper respiratory organs causing mild diseases involved with the viruses named HCoV-229E, HCoV-OC43, HKU1, and HCoV-NL63. Another kind of infections involved in the outbreak during the year 2002 was caused by the virus named SARS-CoV. In the third outing, the outbreak happened during the year 2012 caused by the MERS-CoV. These caused infections towards the lower respiratory tract causing Severe Respiratory Syndrome (SRS). The latest outbreak or in other words pandemic situations is caused by the current outing of the SARS virus causing huge loss not only in terms of money but also in terms of lives. This virus has caused a deadly effect in almost all the countries in the world and on Feb 28, 2020, WHO raised and declared the current situation as a global risk due to COVID-19 to its highest level (COVID-19 Situation Report 39, WHO). This 2019-nCoV (novel beta coronavirus) causes a cluster of severe acute respiratory syndrome and causes high ICU admission with a huge mortality [5]. An immense amount of research is going on to control and create a vaccine that can help to fight against the virus within the human body.

One of the important steps in the application of the computer vision and artificial intelligence can be towards the effective screening methodology in the detection of the infected patients and the regions of severity from the radiological imaging of the chest radiography [6] and computed tomography [7]. The cause for the development of these research areas towards automatic detection techniques came into the picture to leverage the time and decrease in the diagnosis period that is taken by the usage of the gold standard method for detection of COVID-19 which is PCR or Polymerase Chain Reaction. This standard method is highly sensitive, laborious, and is very complicated for the manual process to happen in a very short time. To tackle the time, an alternative screening method using computer vision techniques can help in providing similar results with less time that provides the medical practitioners to gain over time and treat more patients. The availability of radiograph imaging and computerized tomography or computed tomography (CT Scans) can be used as a secondary step towards the infectious region determination in the lungs and nearby regions to understand the impact of the virus better in the patients diagnosed with COVID-19 to the PCR techniques used for determination. These deep learning and computer vision methods which try to extract the important features out of the images and then train a model to get the classification results in better accuracy are employed for these scenarios. In this era of evolving technical solutions towards the field of artificial intelligence, a greater amount of research is being done in the field of medical sciences that would try to detect the facts from images and solve towards the detection with an improved time [8,9]. Some of the relevant studies involve and not limited to the field of diagnosis and understanding of the pulmonary nodules [10,11], classifying the malignant and the benign tumours [12], analysis of the pulmonary tuberculosis with the disease prediction [13,14] etc. In this research, I propose a network called Automatic Diagnostic Medical Analysis for the COVID-19 Detection System (ADMCDS), that takes the images and tries to find the infectious regions to help the doctor better identifying the diseased part if any. I explain a two-stage deep neural network consisting of deep convolutional neural network architecture to automatically detect the severity of the conditions based on the images that are provided to train and understand the hidden features from the X-Rays and the CT scans reports. I have taken into consideration different data sources available in the literature and the research on these fields to make an automatic detection methodology which will give the doctors the options to identify the areas of the interest and take necessary steps and identify. The convolutional neural networks that I have employed has been tested with different kinds of pre-trained networks/ architectures such as ResNET50-50V2, InceptionV3, VGG16-19, InceptionResNetV2, DenseNet169-121-201, NASNet, and MobileNet. The classification layer that is built with this is a fully connect 3 layered neural network with SoftMax function to deal with the binary classification of the COVID-19 patients from healthy patients with higher precision as well as accuracy.

In the following sections, I will explain about the researches that have been going on in the field of computer vision aided medical solutions towards the COVID-19, then follows with the methodology for building the whole architecture and then with the results and analysis of different algorithms involved in the explanation of the approach.

2. Literature Review and Related Research

In a research towards the determination of the misdiagnosis rate in the coronavirus disease 2019 by the radiologists, a study was done with 51 patients who were diagnosed with the COVID-19 infection that was being confirmed by nucleic acid test [15]. In this, it was observed that the chest CT had a low missed rate for the COVID-19 diagnosis which counted to 2/51.

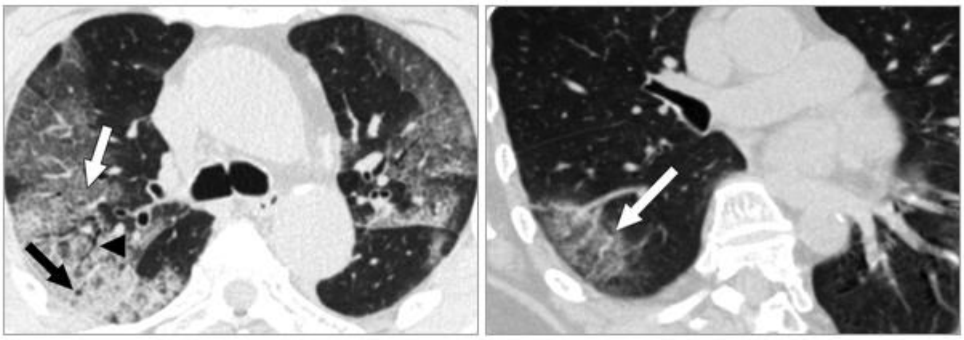

Figure 1: a) In some of the findings of the research, it was found that multiple opacities and thickened intralobular with interlobar septum in case of the 77-year-old woman b) In another findings, ground-glass opacities with vascular enlargement for the 61-year woman with the coronavirus infections

To provide the best diagnosis for novel coronavirus detection using the CT scans, a study was done which included around 1000 patients whose analysis with radiology including the chest CT scans performed better than the lab testing [16,18]. In the absence of certain vaccines and therapeutic drugs, early detection of diseased patients can help in flattening the curve a lot. These results proved that the imaging techniques such as chest CT can be more reliable and faster with practical results as compared to the RT-PCR techniques. To reveal the extent of damage and nature of the infections in the patients, a research was done that collected cases from 101 COVID-19 patients across the four institutions in China Hunan [17]. The scans provided results for patients having ground-glass opacities (GGO) and certain others had mixed GGO. Some 71% of the patients had lesions with large vascular enlargements. To tackle the detection and identification of COVID-19 cases out of the normal healthy samples and pneumonia samples, a unique convolutional neural network-based deep architecture named as COVID-Net was proposed which created a path for an alternative solution to the standard PCR system to identify the COVID-19 cases [19].

Figure 2: a) An example of the NON-COVID patient b) COVID-19 infected patient's X-Rays

In this above-mentioned research, a total of 16,756 chest radiography images were used to train the COVID-Net which is referred to as CoVIDx. This dataset ranges to be coming from 13,645 patients and the sources of two different data locations. This research tries to make a 3 class classification problem consisting of COVID-19 cases, Pneumonia Cases, and Healthy cases. The sensitivity achieved by this model is 95% for the Normal, 91% for the non-COVID19, and 80% for the COVID-19. The main observation can be the sensitivity to define the performance of the solutions in case of medical research using the Artificial Intelligence Solutions [20,21]. As an explanation to the COVID-Net, the whole architecture looks as below,

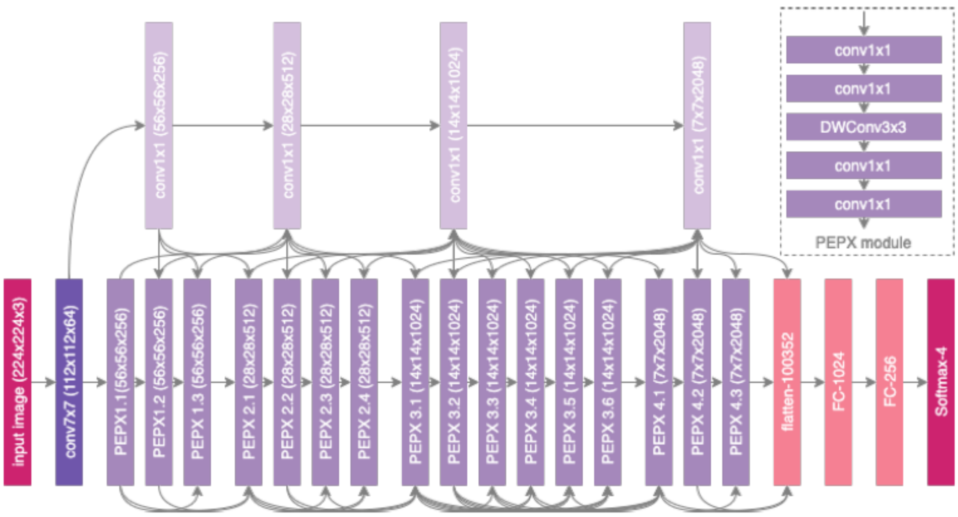

Figure 3: COVID-Net Architecture, usage of the projection-expansion-projection design pattern in this architecture helps in the striking of a strong balance between the computational and representational effectivity

Another deep learning model known as COVNet which is based on the learnings from the visual features extraction from the volumetric Chest computerized tomography or Chest computed tomography (CT Scans) exams helped in the detection of the COVID-19 [22]. The dataset consists of 4356 chest CT scans spanning across 3322 patients. The specificity and the sensitivity for the detection of the COVID-19 is around 90%.

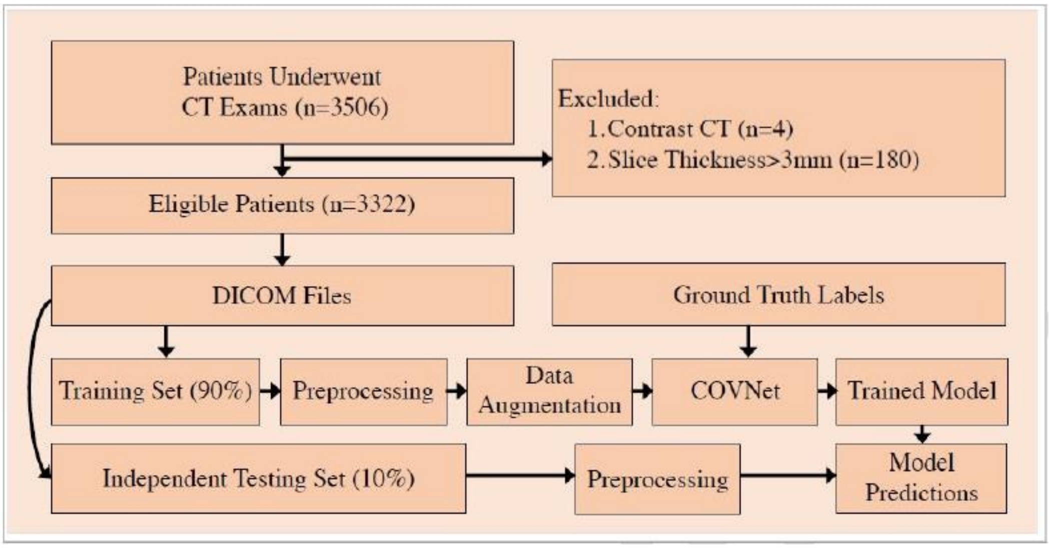

Figure 4: The whole architecture of the COVNet explaining from the Patients Data collections to the model performance and prediction

For automatic detection of coronavirus disease from the X-Rays Images, a Deep Learning Neural Network was analyzed with various kinds of the pre-trained algorithms [1]. In this research work ResNet50, InceptionV3 and Inception-ResNetV2 were analyzed using 5 fold cross-validation, and then the results were checked to see the validity of the model. The pre-trained ResNet50 model outperformed with the highest classification performance of 98%. This proposed solution tried to explain about the no-manual intervention for the feature extraction and COVID-19 detection can be best detected using the X-Rays imaging. To screen the coronavirus infections, another deep neural network architecture proposed which was trained from 618 transverse section (TS) CT samples which included 219 images from 110 patients with COVID-19 positive [23].

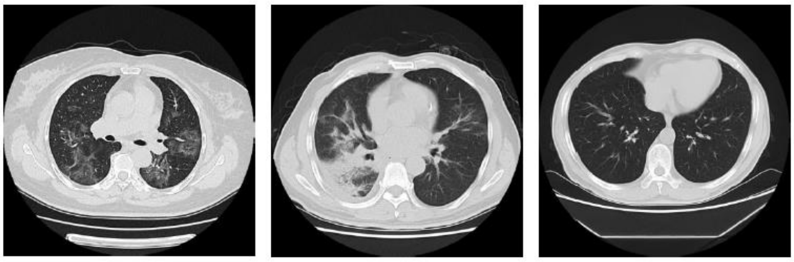

Figure 5: Transverse Section of the CT Scans representing a) COVID-19 positive patient b) Influenza- A pneumonia c) Healthy

The overall accuracy rate that is achieved by this method is 86.7%. A unique patient's monitoring system and

COVID-19 automatic detection using AI was proposed that involved CT scan images and the model achieved an accuracy of 0.996 AUC on Chinese control and infected patients [24].

In all the above works, it has become evident that using the standard AI techniques empowered with the deep Neural Networks employing the standard CNN architectures and combining the system with the medical imaging systems can provide encouraging results which will not only detect the most minute details rather will also help the doctors and other medical practitioners to have more time to treat more number of patients. In this pandemic situation, where the United States and European countries are facing a lot of losses in human lives, this empowered AI solution can be a boom. It will not ask the doctors to treat and choose between a 70+ aged and a young rather give ample amount of time to treat them both after being saving a lot of time during the initial diagnosis.

3. Methodology and Implementation

Most of the solutions that have been discussed above encircles around the solutions being developed with either CT scan images or X-Rays images. In this case, the proposed architecture tries to classify the images based on their nature or based on the input provided by the doctor and then take that particular channel. In this research the pre-trained networks/ architectures such as ResNET50-50V2, InceptionV3, VGG16-19, InceptionResNetV2, DenseNet169-121-201, Xception, NASNet and MobileNet are used. The classification layer that is built with this, is a fully connected 3 layered neural network with a SoftMax function to deal with the binary classification of the COVID-19 patients from the healthy patients with higher precision as well as accuracy. The following image talks about the basic steps for any computer vision project work.

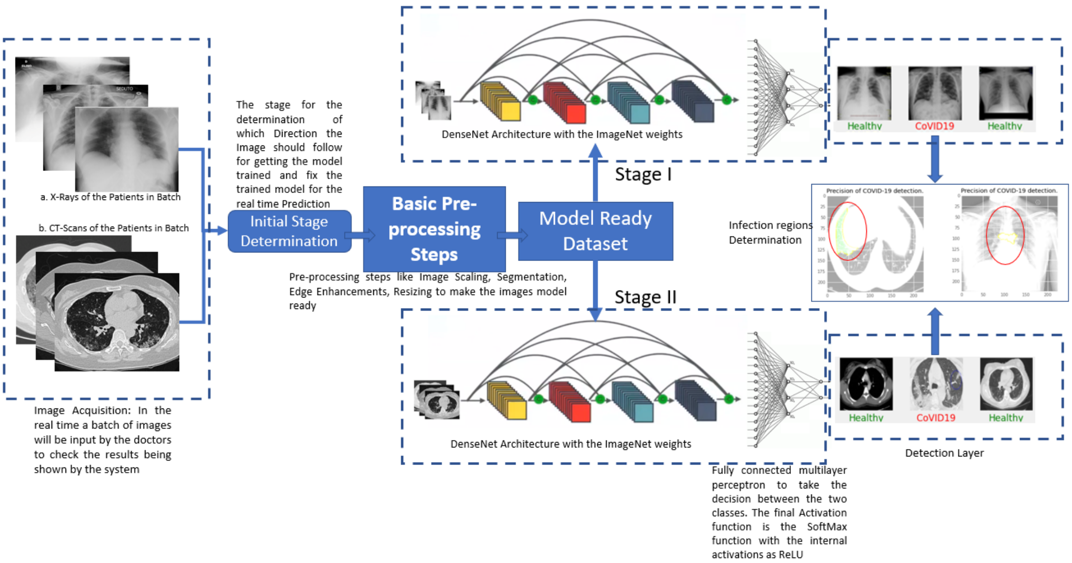

Figure 6: Automatic Diagnostic Medical Analysis for COVID-19 Detection System (ADMCDS), Network Architecture. The network consists of two stages for the determination of whether the classification to be done based on the CT-Scan images or the X-Rays images. DenseNet is fixed based on the results achieved by the architecture in the OOS data

3.1 Image Acquisition

The images can be used here from the sources that capture the medical imaging. In this case, the X-Rays and CT Scans both the systems can be used to take the images and accordingly the particular path to be taken in the process. For the model building, the datasets that are used consist of CT Scans and X-Rays of the patients that are used by different researchers to work on the building of the model. The first set of the data is taken from the GitHub repository by Dr Joseph Cohen and the Kaggle Pneumonia Challenge Datasets [25,26]. In the first case, there are in total 152 images which consist of different cases of the infections that include ARDS, SARS, Pneumocystis, Streptococcus along the COVID-19. Since I only look into the data consisting of the COVID-19 as the primary case, the filtration of the images was left with 122 images. From these 122 images, I do have different sources of data either from CT Scans or X-rays. Hence these two sources need to be separately handled in case of the architecture that I have built up. When the X-Rays are filtered out, the amount of the data left is 100 and rests with CT-Scans. Although the data is very less in number, they can be a good decisive path for checking our model performance. Also, this data had a little amount of healthy patient details and for the same to happen it is needed to mix some of the healthy data into it. I randomly took some of the images from the Kaggle Pneumonia dataset to make a sample of the datasets for the training and testing of the model. The second source of data for the X-Rays model building came from the roboflow.ai [27]. This dataset consists of a total of 5887 images with different classes i.e. COVID-19, Pneumonia, and Healthy. Since I considered for the determination of the COVID-19 cases out of the healthy, I took only the COVID-19 and Healthy cases out of it. Although, the system is agnostic to the different kinds of data that can be input, for the model building using the CT Scans data, I used the data set COVID-CT [28]. This dataset consists of 349 CT images from 216 patients which are considered to be positive.

3.2 Stage Determination

For determining the kind of images that needs to be input to the model, this first version give the medical practitioners an option to upload the images to the particular stage for the model to take place. For this scenario, the model has the options given for the doctors to upload in the case of the X-Rays stage if they want to consider the analysis using the X-Rays reports and CT-Scan stage if they want to consider the analysis using the CT-Scans reports. Automation can also be done to avoid manual intervention.

3.3 Pre-Processing and Model Readiness

The first step for any of the image pre-processing techniques goes through the image resizing in which the images were made to re-size to a particular dimension irrespective of the kind of sizes that they were having initially. The image size that is considered over here is 224 and python's cv2 package along with skimage was used to process the same. The images were then normalized using the mean subtraction and scaling. To achieve this, channel-wise mean (μ_R, μ_G, μ_B) used similar to the one done in the ImageNet dataset. This can be done by applying the normalization in every channel using some scaling factor α.

$$R^{`} = \frac{R - \mu_R}{\alpha_R}, G^{`} = \frac{G - \mu_G}{\alpha_G}, B^{`} = \frac{B - \mu_B}{\alpha_B} \tag{1}$$

Here, $R^{`}, G^{`}, B^{`}$ are the processes RGB channels for the input image.

3.4 Modelling

For selecting the best of the architecture with the pre-trained weights, different architectures were used from ResNET50-50V2, InceptionV3, VGG-16, InceptionResNetV2, DenseNet169-121-201, NASNet, and MobileNet.

3.4.1 ResNet

Two variants of ResNet architecture was used in this case, ResNet50 and ResNet50V2. The key idea behind the ResNet is the identity shortcut connection [29]. The flow of the ResNet Architecture is shown as below,

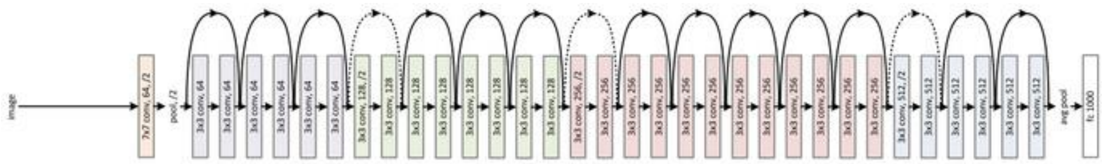

Figure 7: ResNet Architecture with the identity shortcut connection that skips one or more layers

3.4.2 Inception

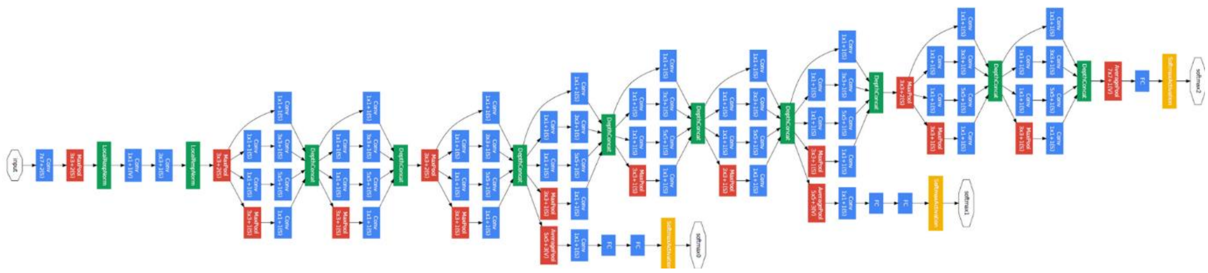

Figure 8: GoogleNet or Inception Architecture

It contains 1×1 Convolution in the middle of the network. And global average pooling is used at the end of the network instead of using fully connected layers. These two techniques are from another paper "Network In-Network" (NIN) [30]. Another technique, called the Inception module, is to have different sizes/types of convolutions for the same input and stacking all the outputs.

3.4.3 DenseNet

CNN is playing a dominant role in today's world's imaging technology [31]. From object detection, recognition to semantic, and instance segmentation, CNN can be used to solve a wide variety of problem statements [32]. Features from images are extracted on CNN by taking repeated convolutions using kernels, which are usually called standard ConvNets as shown in figure 9 [33].

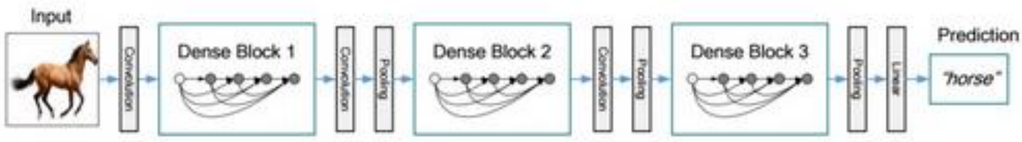

Figure 9: An example of the DenseNet with 3 dense blocks. The real DenseNet network is shown in the Network Architecture

3.4.4 VGGNet

In this network, the effect of the depth in the convolutional neural networks on the accuracy is analyzed through the large scale image recognition setting [34]. This Architecture uses a very small convolutional filters which is of 3X3 and hence finds a very optimal and significant improvement to the prior settings. The depth used in this analysis is with VGG-16 and VGG-19 with more preferably VGG-16 architecture using the ImageNet's weights.

Figure 10: Architecture of VGGNet

3.4.5 NASNet

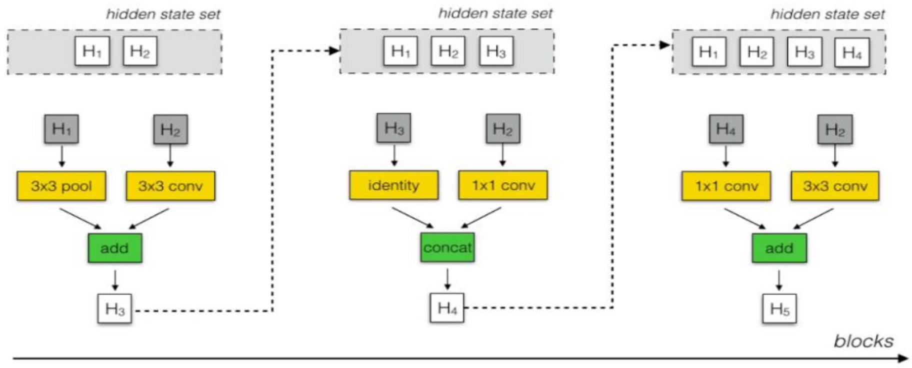

Figure 11: NASNet Architecture using the Reinforcement Learning

In NASNet, though the overall architecture is predefined, as shown above, the blocks or cells are not predefined by authors. Instead, they are searched by the reinforcement learning search method [35].

3.4.6 MobileNet

Depth wise Separable Convolution is used to reduce the model size and complexity [36]. It is particularly useful for mobile and embedded vision applications.

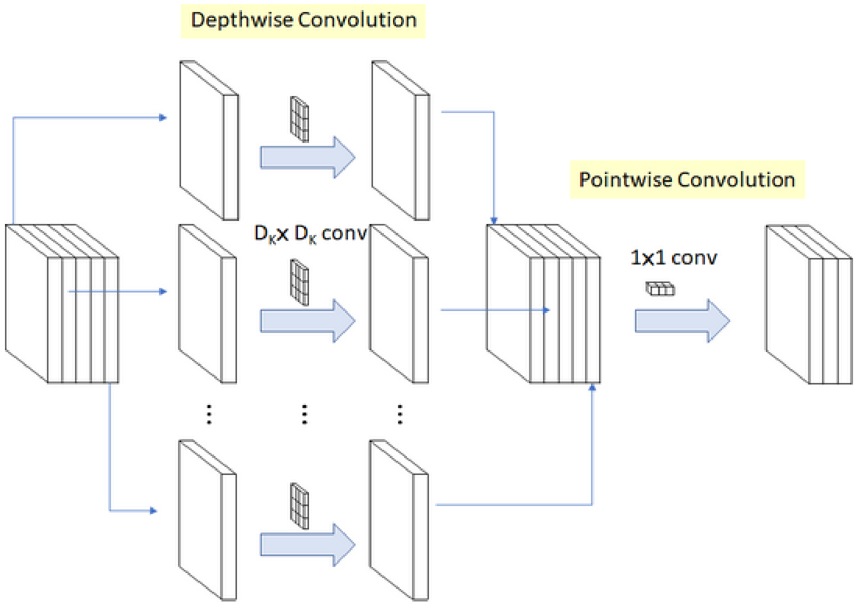

Figure 12a: MobileNet Architecture

3.4.7 Xception

Xception by Google [37], stands for the Extreme version of Inception. With a modified depthwise separable convolution, it is even better than Inception-V3 for both ImageNet ILSVRC and JFT datasets.

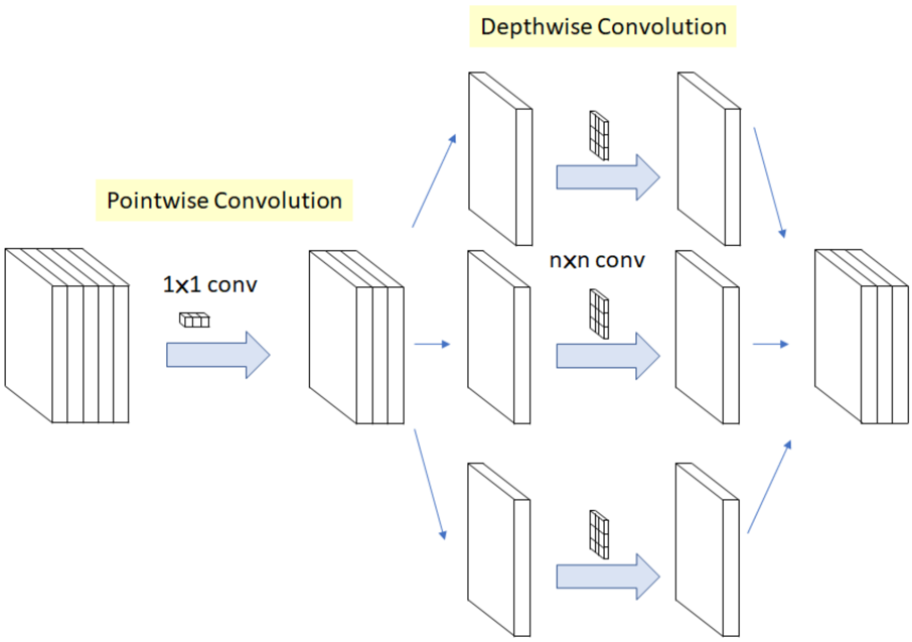

Figure 12b: A Modified with Separable Convolution used for the Inception Module called an Xception with the "extreme version of the inception model"

In the above architecture, the main concept behind the usage of the techniques in this detection of the COVID-19 prediction is the Transfer Learning. Since to generate better accuracy and having less training time, the pre-trained networks can be re-used for a different cause. In this scenario, although the Network is the pre-trained networks, but for the classification and the decision making a second network can be used. Here, I have used Fully Connected Neural Network for the decision making for the COVID-19 cases from the Healthy cases.

Once the above model is done, the fully connected layer for the decision for whether the image is belonging to COVID19 or not is built using 3 layered Feed Forward Network with 1024 neurons in the first hidden layer, 512 in the second hidden layer and 64 in the third hidden layer. The Base model has initially feed the input to the MLP using Average Pooling 2D and before the output use, Global Average Pooling 2D.

4. Results and Discussion

The datasets that have been taken into consideration, will be used to verify and build the best performing algorithm. For training the model, I have used 75% of the dataset for the model weights setting and 25% for the validation of the model. For building and testing the model, I used Google Colab with the GPU instance. For testing the model performance in the real-time scenario, I used Intel Core i7 with a 2.70GHz processor with 8GB RAM and with GEFORCE 940MX GPU (4GB). For the first dataset, the number of X-rays samples present in the data was 1652. Out of which 69 X-rays samples were with COVID-19 positive and the rest were healthy. Since the data that has been considered was of one particular type. The data filtration was done for the X-rays which were of posteroanterior or PA type.

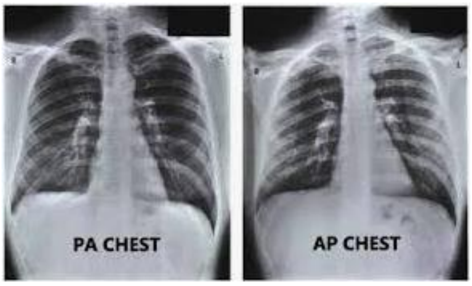

Figure 13: Example of the different views of the X-Rays

A sample of the results for the first Dataset is as shown in the below figure,

Figure 14: Sample output image is shown from the model output

For the second dataset, the total number of images that were taken into consideration were 158 images for COVID-19 positive patients X-rays and 1958 Normal images X-rays datasets. The first set of cleaning that was done from the original raw dataset was by removing the different other system sources of the dataset. In such a scenario, it's advisable to remove the CT-scans datasets and some of the different views of the X-rays datasets. Among the left out, some of the images which were hazy and not clear were also removed from the dataset building. The third source of the dataset was made by the merging of the prior two sources of the datasets. The important factor here is that the model gets a lot more amount of positive cases to deal with than the original data and hence the model performance also increase and can be seen from the analysis of the results. In the merged dataset (Dataset 3), I have kept some of the images that can be taken into consideration for the out of sample test. I have used 15% of the data for the OOS for validating the trained model or the fitted model in the training data. In the case of the OOS sample, 44 data were COVID19 positive and 532 were Healthy data. This can be thought in the way that the doctors or the medical practitioners are using the model while doing real-time testing. The model comparison is shown in the below table.

Table 1: Results Comparison of all the pre-trained architectures with the Fully connected Neural Network. The Pre-Trained algorithms use ImageNet weights.

	Dataset 1			**Dataset 2**			**Dataset 3**			**OOS**		
Architecture	**Sensitivity**	**Specificity**	**Accuracy**	**Sensitivity**	**Specificity**	**Accuracy**	**Sensitivity**	**Specificity**	**Accuracy**	**Sensitivity**	**Specificity**	**Accuracy**
VGG16	1.00	**1.00**	**1.00**	0.988	**0.775**	**0.972**	0.993	0.729	0.977	0.996	0.618	0.974
ResNet50V2	0.998	0.706	0.986	1.00		0.924	0.971	**0.875**	**0.965**	0.970	**0.824**	**0.961**
DenseNet169	1.00		0.959	1.00	0.750	0.981	0.981	**0.938**	**0.979**	0.991	**0.941**	**0.988**
DenseNet201	0.995	**0.941**	**0.993**	0.992	**0.800**	**0.977**	0.996	0.729	0.980	0.998	0.765	0.984
DenseNet121	1.00	**0.882**	**0.995**	1.00	0.700	0.977	1.00		0.940	0.998	0.765	0.984
InceptionResNetV2	1.00		0.959	1.00		0.924	1.00		0.940	1.00		0.940
InceptionV3	1.00		0.959	1.00		0.924	1.00		0.940	1.00		0.940
NASNetMobile	1.00	0.588	0.983	1.00		0.924	0.987	**0.792**	**0.975**	0.993	0.765	0.979
MobileNet	1.00		0.959	0.998	0.500	0.960	0.988	**0.854**	**0.980**	0.983	**0.941**	**0.981**
VGG19	1.00	0.529	0.981	0.988	0.700	0.966	0.988	**0.750**	**0.974**	0.987	**0.794**	**0.975**
Xception	1.00	**0.824**	**0.993**	0.926	**0.900**	**0.924**	0.985	0.708	0.969	0.998	**0.794**	**0.986**

In the above analysis, I have used all the pretrained algorithms to check and analyse the results and check which model performed well in case of the OOS dataset. If the first dataset is analysed, no doubtfully VGG-16 network outperformed all other models. In the case of the second dataset, Xception Architecture performed well in identifying COVID19 cases, and hence according to the theory of the model building for the patients who are determined as the COVID, can directly be sent for getting treated. Since these amount of summed up patients, time can be used by the medical practitioners and doctors additional patient's check-up. Here, the accuracy is not given the most important factor since this a healthcare area and the data is imbalance but it can't be neglected either. Xception got 90% correct predictions correct in the COVID19 positive cases while for predicting the Normal or the Healthy cases, it predicted with 92.6% accurately. A comparative performance can be found to be shown by DenseNet201 architecture. It predicted with 80% for the COVID19 positive cases and 99.2% accurately in the case of the Normal cases. The dataset 3 performance is important not only to judge the best performing algorithm but also to see, which model is kind of stable in terms of the model behaviour across the time with the increase in the dataset. When checked on the dataset 3 performance, DenseNet169 performed well in case of both the validation as well as the OOS. In the case of the Out of Sample data, DenseNet accurately predicted with 94% for the COVID19 cases and 99% for the Normal or Healthy cases while in the case of validation sets, with 93.8% and 98% for the COVID19 and Normal respectively. Comparative results are also done with the architectures ResNet50V2, MobileNet, and VGG networks.

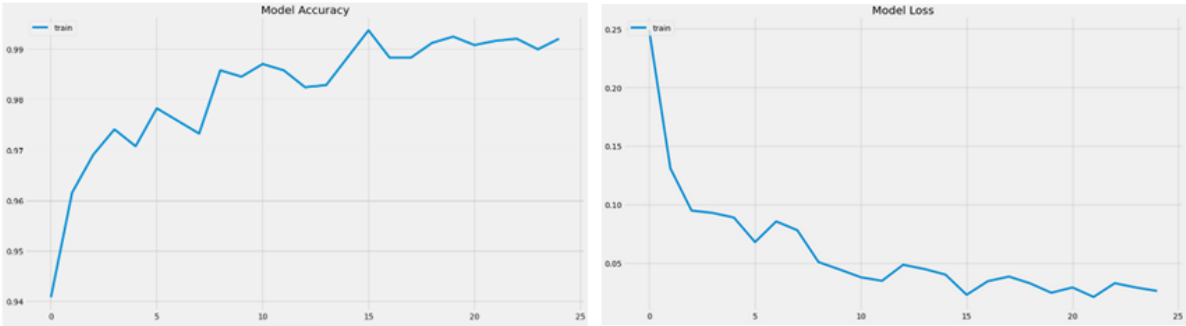

Figure 15: DenseNet169 Model Accuracy curve and Model Loss curve with the number of the epochs

The Confusion Matrix for the model DenseNet169 on the OOS data is shown in the below figure,

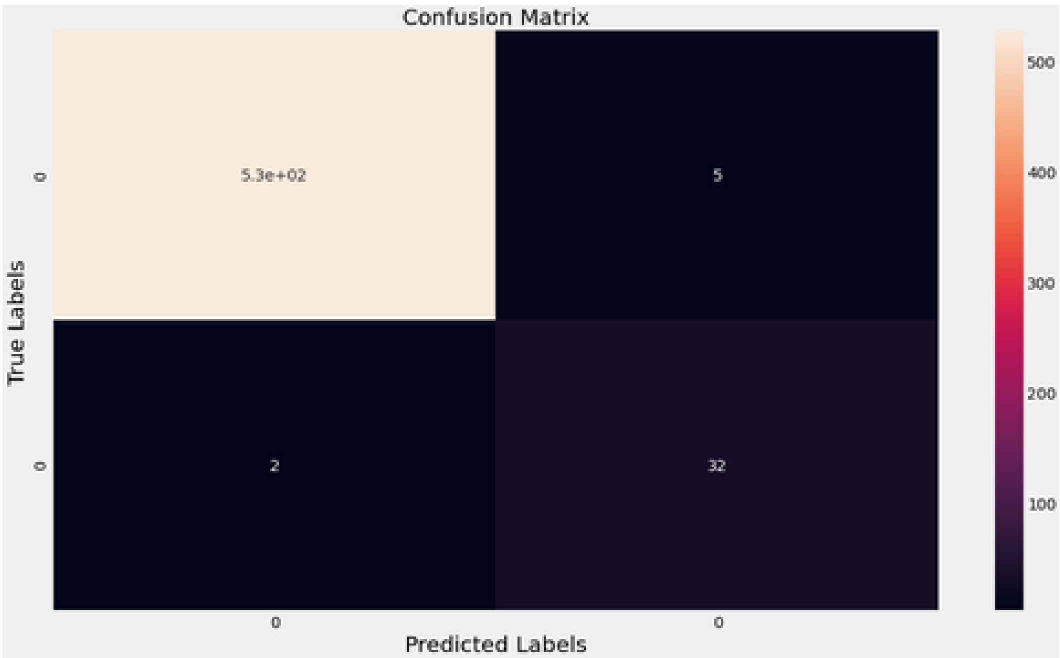

Figure 16: DenseNet169 OOS Confusion Matrix

As seen in the above confusion matrix, DenseNet169 predicted 32 out of the 34 COVID19 positive cases in the real-time scenario and 532 Healthy cases out of 537 samples present in the real-time. The next step for the checking of the severity detection for the model in case of the infectious or in other words in terms of the model behaviour the features in case of the decision making are done using the LIME package in Python.

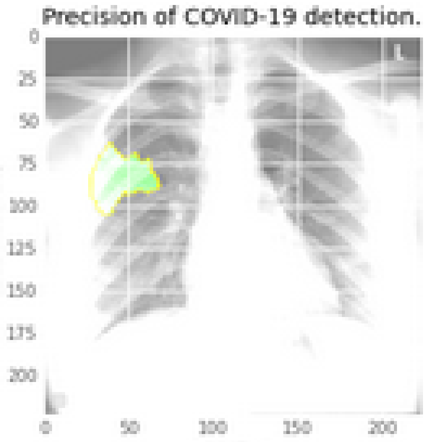

Figure 17: The infection region or the Decisive features taken for the particular image. In this case, the last layer features extraction is tried to map to the original image to make the region highlighted

As discussed about the first stage of the model that uses the X-Rays images and predicts on the model in predicting the images for any particular class in the real-time taking into the consideration of the way doctor tries to mimic the scenario, here let's move to the model building part using the CT-Scans. The sample of the images that were being input to the model is as below,

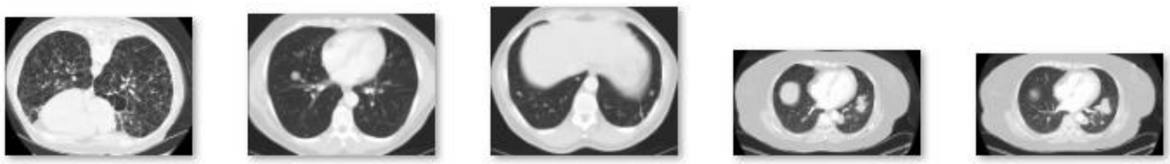

Figure 18: Sample images that are to be input to the model building using the CT scan images

The whole purpose of building a 2-staged or multi-staged model with and for different kinds of images is that the images possess different information with different kinds of the view of the images. The same is for this particular solution to the product. Here, as well I used the Holdout method for the model sample building for training and testing for the fixing and fitting the parameters of the predicting model. The dataset that is being used for the case of the CT scan images were from the CT_COVID data. This data consists of 146 COVID19 positive images and 397 Healthy or Non-COVID19 CT Scans images. The OOS dataset consists of 22 COVID19 cases CT scans that was filtered from the dataset 2 from the X-Rays dataset mentioned above. If the model performs the best in the validation set of the model building and the OOS then the model can qualify for performing better in the CT Scans dataset. In the below table let's compare the performance of different architectures. For the training, I used 75% of the data and 25% for the testing set.

Table 2: Results Comparison of all the pre-trained architectures with the Fully connected Neural Network. The Pre-Trained algorithms use ImageNet weights

	Dataset			OOS		
Architecture	**Sensitivity**	**Specificity**	**Accuracy**	**Sensitivity**	**Specificity**	**Accuracy**
VGG16	0.94	0.62	0.85		0.773	0.773
ResNet50V2	0.990	0.487	0.853		0.000	0.000
DenseNet169	0.899	0.649	0.831		**0.909**	**0.909**
DenseNet201	0.849	**0.811**	**0.838**		**1.00**	**1.00**
DenseNet121	0.869	**0.865**	**0.868**		**1.00**	**1.00**
InceptionResNetV2	0.84	0.757	0.816		0.364	0.364
InceptionV3	0.76	0.784	0.765		1.00	1.00
NASNetMobile	0.88	0.460	0.765		1.00	1.00
MobileNet	0.87	0.811	0.853		0.091	0.091
VGG19	0.86	**0.865**	**0.860**		**1.00**	**1.00**
Xception	0.95	0.514	0.831		0.500	0.500

In the above table during the model building, in the test set, DenseNet121 performed the best with 86.5% of specificity or predicting the COVID19 Cases which were 37 in number. The accuracy of the DenseNet121 was also better than all the other algorithms. Now when the Out Of Sample was taken into consideration, all the 22 COVID19 positive CT scans was predicted perfectly. Although the same was done perfectly by many other algorithms like DenseNet201 and VGG19, but the performance of DenseNet121 can be considered to be the best in the case of the Test sample set of the data. Comparative results were also given by DenseNet201 and VGG19 architectures which performed similarly good.

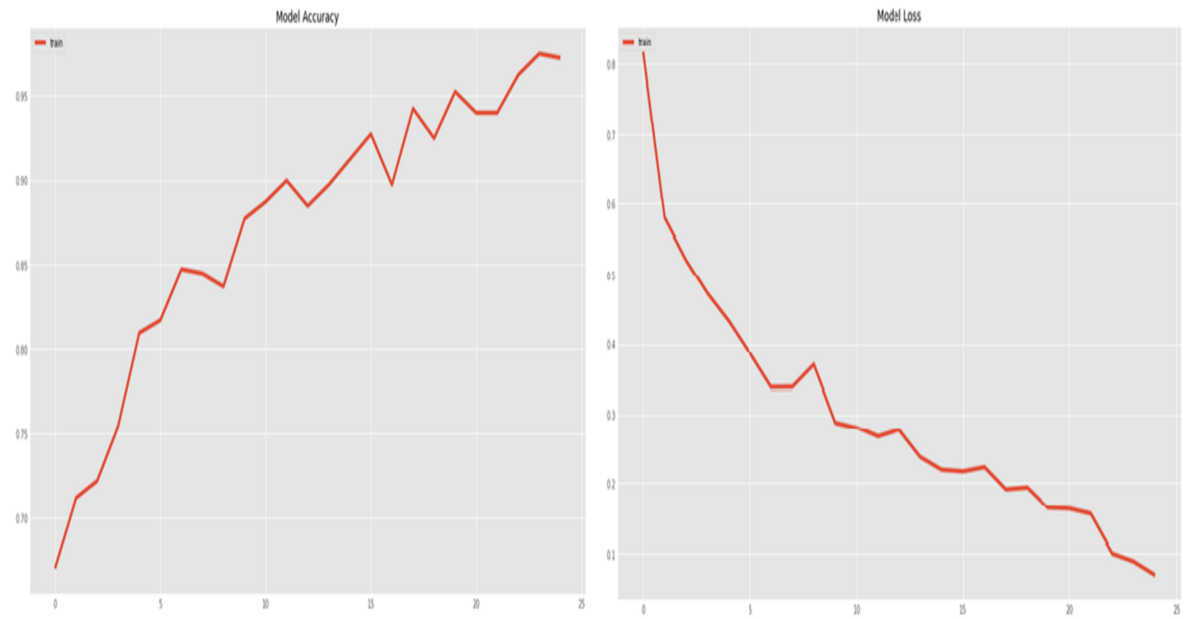

Figure 19: DenseNet121 Model Accuracy curve and Model Loss curve with the number of the epochs

Since the model has performed exceptionally well in the OOS data, the Confusion Matrix is with only one cell i.e. the prediction for 22 COVID-19 positive patients is 22.

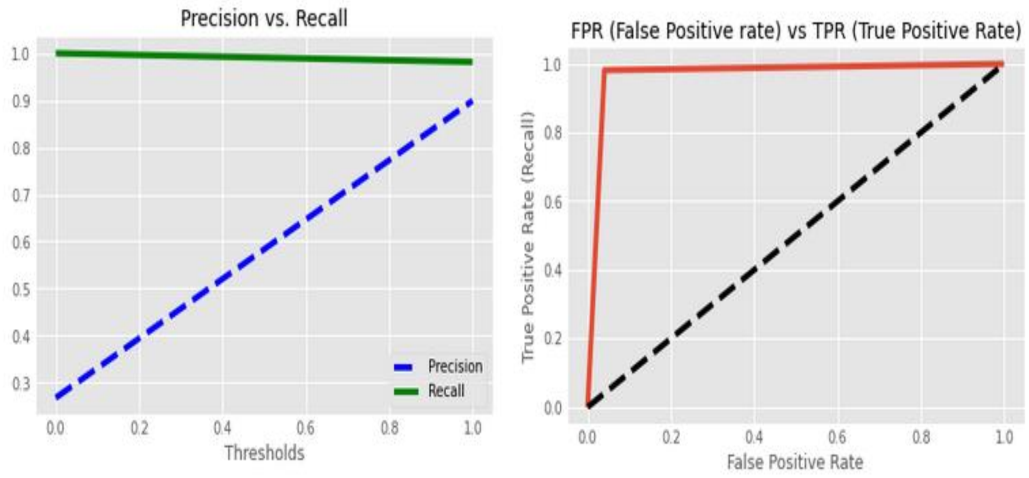

Figure 20: DenseNet121 model building different metrics a) graph showing the variation of Precision against the Recall b) FPR Vs TPR

In the results for the CT scan as an output from the model, the output looks like as below,

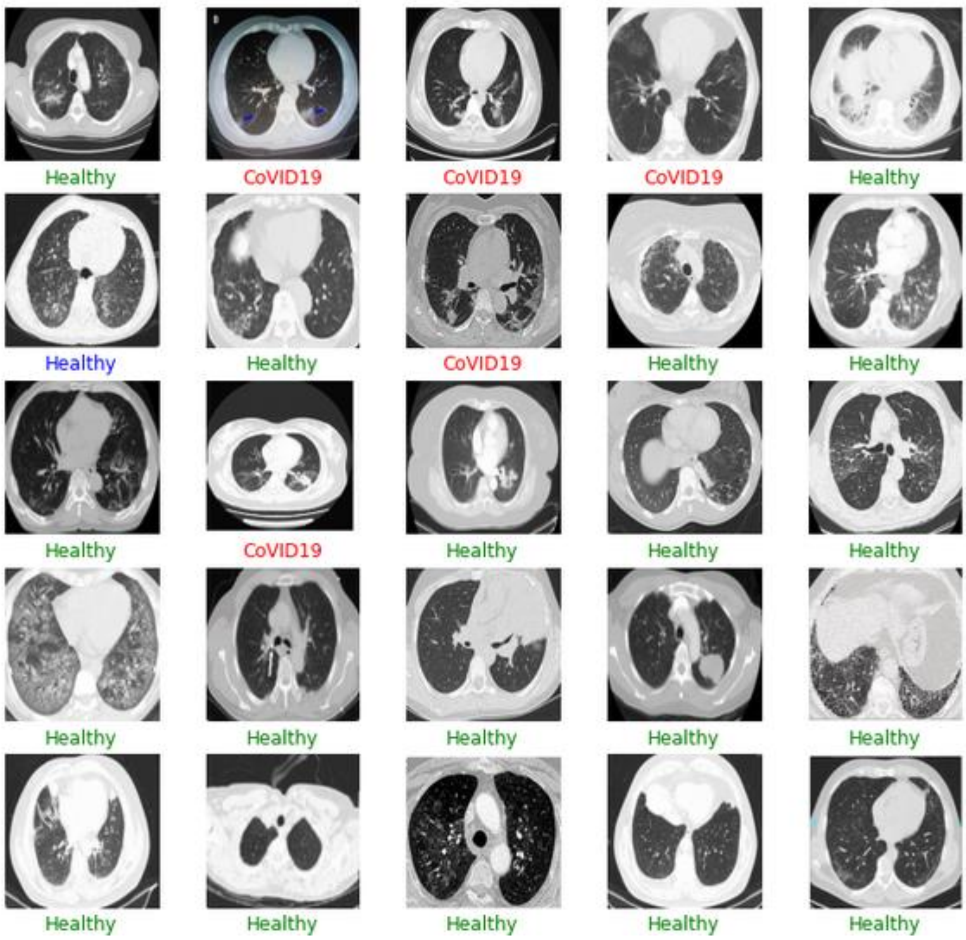

Figure 21: Sample output with the test/validation sample. Green colour shows the Healthy, red colour tells the COVID19 prediction and Blue colour talks about the uncertainty in the prediction

Similarly to the X-Rays the infectious regions or the decision features are shown below with the help of the LIME package and the heat map was then generated. The decision was taken using the last layer of the feature extraction from the pretrained layers.

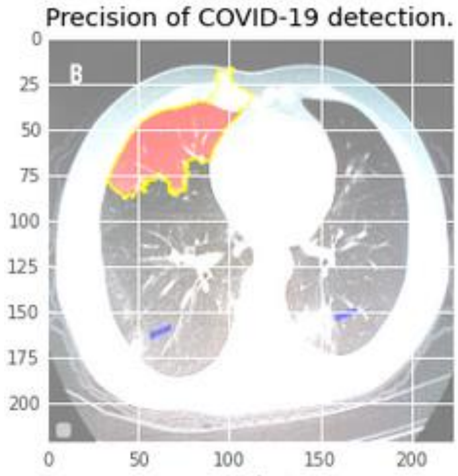

Figure 22: Decision features heat map in the original CT Scan using the information from the last layer of the pretrained algorithm

5. Conclusions

In this whole analysis, the main purpose to have the solution which is Automatic Diagnostic Medical Analysis for COVID-19 Detection System (ADMCDS) is to help a doctor in a way to increase the diagnosis time so that many patients are treated in this high emergency time where tens of thousands of people are reported to be succumbed to the infections due to SARS-CoV2 every day throughout the world. In this pandemic situation [38], time and a place in hospital is more important for saving the lives of the infected patients. The model is in no way to replace a doctor nor can decide a doctor which has many other factors that impact a decision at a particular point of time. This whole system can make the life of a doctor a bit easier in giving some small suggestions, that it has got itself trained from the thousands of the data that is being fed into it. The data is always a very important factor for any AI or machine learning model building. As the COVID19 is a sudden and recent emergency case, the data sources are hence very less. But this whole system can work better when fed with more data and can prove beneficial in real-time which we have already seen in the results section. As explained above the idea is tested with the data to a lot of pretrained algorithms and found out that DenseNet performed well in both the OOS datasets. The reason can be due to the strong gradient flow, computational and parameter efficiency, extraction of more diversified features with maintaining low complexity features. We saw that DenseNet Architecture in case of the X-rays performed with predicting 32 out of the 34 COVID19 positive cases in the real-time scenario and 532 Healthy cases out of 537 samples present in the real-time and case of the CT-Scans, it performed with 86.5% of specificity or predicting the COVID19 Cases which were 37 in number.

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