

DETECTION AND SEGMENTATION OF COVID 19 USING CT SCAN IMAGE

*A minor project report,
submitted in partial fulfillment of the requirement for the award of*

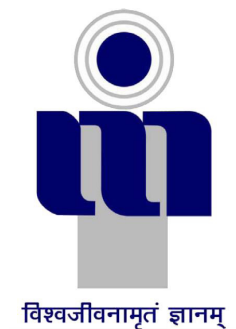
B.Tech. degree in Information Technology

by

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CANDIDATES DECLARATION

We hereby certify that the work, which is being presented in the report, entitled **Detection and Segmentation of COVID 19 Using CT Scan Image**, in partial fulfillment of the requirement for the award of the Degree of **Bachelor of Technology** and submitted to the institution is an authentic record of our own work carried out during the period *July 2020 to October 2020* under the supervision of **Dr. Gaurav Kaushal** and **Prof. Manisha Pattanaik**. We also cited the reference about the text(s)/figure(s)/table(s) from where they have been taken.

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ABSTRACT

Early detection of 2019 novel coronavirus disease (COVID-19) is essential for disease cure and control. In comparison with reverse-transcription polymerase chain reaction (RT-PCR), chest computed tomography (CT) imaging may be a significantly more trustworthy, useful, and rapid technique to classify and evaluate COVID-19, specifically in the epidemic region. Almost all hospitals have CT imaging machines therefore, the chest CT images can be utilized for early classification of COVID-19 patients. In this research paper, various Deep CNN based approaches are applied for detecting the presence of COVID19 from lung CT images. A decision based approach is also proposed, which combines predictions from multiple individual models, to produce a final prediction. Experimental results show that the proposed decision fusion based approach is able to achieve above 86% results across all the performance metrics under consideration, with accuracy and F1-Score being 0.883 and 0.867, respectively. The experimental observations suggest the potential of such Deep CNN based approach in real scenarios, which could be of very high utility in terms of achieving fast testing for COVID19. After classification of CT scan image into COVID Positive OR COVID Negative, then segment those infected region which get infected through coronavirus

Keywords: Deep learning, COVID-19 Detection and segmentation, lung CT Scan

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ABBREVIATIONS

CNN	convolutional Neural Network
CT	Computed Tomography
DL	Deep Learning
RT-PCR	Real-Time Polymerase Chain Reaction
+VE	Positive
-ve	Negative
ResNet	Residual Network

NOTATIONS

$\mu_A(x)$	Membership function of crisp set A
$x_i \in X$	An element x belongs to set X
\triangleq	Nearly equal to
$\max[\]$	Maximum value of variables
$\min[\]$	Minimum value of variables
\wedge	Conjunction

CHAPTER 1

INTRODUCTION AND LITERATURE SURVEY

This chapter includes the details of the background, our problem statement, thesis objectives and literature review related to the work done in this field.

1.1 Introduction

In this section we briefly describe our project that aims to classify a given CT scan image into COVID +ve or COVID -VE .

1.1.1 Background

The Coronavirus Disease (COVID-19) is one of the rapidly communicable infectious diseases, affecting a large number of the population globally. The infection due to COVID-19 largely affects the respiratory tracts and creates a layer of the lesion on the lungs which affects the normal functioning of the lungs. The symptoms of COVID-19 range from dry cough, tiredness, mild to moderate respiratory illness, loss of taste sensation to fever . The disease spreads from a person infected with COVID-19 to another person through the transmission of micro size droplets from the nose or mouth, that is expelled when a person with COVID-19 sneezes, coughs and even speaks. There are very limited amount of ventilators and testing kit available so early detection of COVID 19 through deep learning is very essential .

COVID-19 pandemic has a very large impact on the respiratory systems. Thus, medical imaging features of chest radiography are found to be useful for rapid COVID-19 detection. The imaging features of the chest can be obtained through medical imag-

ing modalities like CT (Computed Tomography) scan and X-rays. The advantages of CT scan over x-ray include

- 3-D view formation of organs in CT scan.
- convenient examination of disease, and its location.

Therefore, for COVID-19 detection, CT scan of the chest is selected for the detection of COVID 19 .

The majority of tests being produced to detect the COVID-19 disease are termed as PCR tests. The steps involved in the PCR test are the collection of a clinical specimen, and sending the samples to the laboratories . The major challenges of PCR test in the COVID-19 rapid detection are as follows:

- insufficient kit for COVID-19 detection/million population.
- PCR test kits take longer duration for diagnosis of disease therefore it is time consuming for getting the results.
- PCR test kit having high false negatives rate.

Timely and accurate treatment of COVID-19 disease is a challenging task for the healthcare givers. But the limited availability of conventional COVID-19 detection kits is a major issue. Thus, an automatic diagnosis model is required for COVID-19 detection using imaging modality to reduce the manual involvement in disease detection using a CT scan of chest images.

1.1.2 Literature Review

Deep learning has proven to be successful in Image classification tasks ranging from object recognition and detection to semantic segmentation. Motivated by these successes, DL has been increasingly used in medical applications, e.g. for biomedical image segmentation [1] or pneumonia detection from lung X-ray [2]. These seminal works indicate that, with the availability of data, DL can lead to the automation of diagnoses which are of significance to medical community.

In the wake of the current pandemic, recent works have focused on the detection of COVID-19 from lung CT . In [3], a U-Net type network is used to track for each suspicious COVID-19 pneumonia region on consecutive CT scans, and a quadrant-based filtering is exploited to reduce possible false positive rate.

CT imaging is a popular technique for the diagnosis of lung diseases [4]. Segmentation of organs and lesions from chest CT slices can provide crucial information for doctors to detect and segment lung diseases [5]. Recently, many works have been provided and obtained a very good result. These algorithms often employ a classifier with extracted features for segmentation in lung CT. For example, Keshani et al. [6] utilized the support vector machine (SVM) classifier to detect the lung nodule from CT slices.

Deng-Ping *et al.* proposed Semi-Seg inf-Net [7] model in which pseudo labelled data is generated through semi-supervised learning as have limited number of data and identify infected regions from chest CT slices. Further Shen *et al.* [8] presented an automated lung segmentation system based on bidirectional chain code to improve the performance. However, the high variation in the position of the infected region makes it difficult for extracting the feature. To overcome this issue, several deep learning algorithms have been proposed to learn [9]. For instance, Wang *et al.* [9] developed a central focused convolutional neural network to segment lung nodules from heterogeneous CT slices. Jin et al. [10] utilized GAN-synthesized data to improve the training of a model for lung segmentation. Jiang et al. [11] designed two deep networks to segment lung tumors from CT slices by adding multiple residual streams of varying resolutions.

The unsupervised anomaly detection and segmentation will detect the anomaly region [12], however, it can not identify whether the anomaly region is related to COVID-19. However, based on the few labeled data, the semi-supervised model could identify the target region from another anomaly region, which is better suited for detection of COVID-19. Moreover, the transfer learning technique is another good choice for dealing with limited data. But currently, the major issue for segmentation of COVID-19 infection is that there are very few datasets for research purpose, but, being short of high quality pixel-level images. Thus, our target is to utilize the limited dataset efficiently and leverage unlabeled data. Semi-supervised learning provides a more suitable solution to address this issue.

For COVID-19 screening purpose, the reverse-transcription polymerase chain reaction (RT-PCR) has been considered as gold standard. However, the shortage of equipment and requirements for testing kit and ventilator, limit the fast and accurate screening of COVID 19. Further, RT-PCR testing is also reported false negative rates [13]. As an complement to RT-PCR tests, the imaging techniques, e.g., X-rays and computed tomography (CT), have been done for detection [14]. Compared to X-rays, CT screening is more preferred due to its three-dimensional view of the lung. In recent studies [13], the typical signs of infection could be observed from CT slices, e.g., ground-glass opacity (GGO) in the early stage, and pulmonary consolidation in the late stage. For in-

stance, Wang et al. proposed a inception neural network [15] for classifying COVID-19 patients and normal . Instead of directly training on complete CT images, they trained the network on the regions of interest, which are identified based on the features of pneumonia. In addition to other network architectures have also been considered in developing AI-assisted COVID-19 diagnosis systems. Typical examples include U-Net , used in [16] ,and ResNet used in [16] . Finally, deep learning has been employed to segment the infection regions in lung CT slices so that the resultant quantitative features can be utilized for large-scale screening [17], and lung infection quantification [18] of COVID-19.

1.1.3 Research Gap

After studying research paper , there are some shortcoming as follows:

- In RT-PCR testing method , first take a sample of patients then send it to laboratory, after some day their result comes so it is time consuming and having high false negative [13]. This method having more manual effort . So their solution is make use of Deep learning . It takes less time
- There are very limited dataset available for research purpose . As many imaging techniques require more number of data . It may occur overfitting situation, from which this model will give more false result for testing case . So their solution is to first generate pseudo labelled data then fit the data into model .
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- In many pre-existing paper[16] they only segment infected region without even knowing a given CT scan image is COVID +ve or COVID -ve . In this research paper first classify a given CT scan image into COVID +ve or COVID -ve by various transfer learning based model ,if patient is found COVID +ve then segment those infected region which get infected through coronavirus.
- The algorithm which is used to in this research paper [7] generate Pseudo labels in this research paper from unlabelled data is very time consuming. According to this research paper mean absolute error is very large so we have to minimize the error.

1.1.4 Project Objective and Deliverables

The main objectives of our project can be summarized in the following points :

- Data Pre-processing phase -
 - Convert image - In this phase all the given image are converted into single format (.jpeg) format .
 - Resizing image - In this phase all the image are resized it according to what model required.
 - Normalization of image- All the image are normalized [0,1] so that uniformity will maintain.
- Data Augmentation phase - There are limited number of dataset available for research purpose so we have to increase the data by various shear operation ,translation ,rotation operation .
- Detection of COVID 19 - In this phase classify a given CT scan image into COVID +VE OR COVID -VE by various pre-trained model and then make a decision on these models to detect COVID 19.
- Segmentation of infected region -After classification of given a given CT scan lung image into COVID +VE OR COVID -VE , if a patient found COVID +VE then segment those infected region which get infected through coronavirus

1.1.5 Problem Statement

The problem is to first classify a given CT scan image into COVID +VE or COVID -ve by various transfer learning based model and select best model , after that if a given CT scan image is COVID +VE then segment those infected region which get infected through coronavirus.

1.1.6 Transfer Learning for COVID 19 Classification

The term that is used in Transfer Learning in the area of machine learning tells that the knowledge learned in some task, apply it on other related task.It is one of those strategies used for training a deep neural network where data set is very low for training .It is pre-trained model that is trained on Imagenet data set of a very big quantity of data, that classify these data set into thousand classes .

The reason behind using transfer learning for COVID 19 detection is :

- less pre-processing of the dataset is required.

- It has faster-learning process.
- time complexity can be adjusted by decreasing the numerous parameters
- works well on the limited data set.

In the proposed work, transfer learning is used for binary classification of Lung CT scan images into COVID-19 and Non-COVID. For this, four different pre-trained transfer learning-based CNN models are used, namely, ResNet18, ResNet50, ResNet101, and SqueezeNet. Basically These pre-trained CNN models are trained to classify into 1000 object categories from the image net data set . The pre-trained transfer learning models are retrained for the binary classification data of a lung CT scan into 2 classes.

CHAPTER 2

DESIGN DETAILS AND IMPLEMENTATION

This chapter discusses the intrinsic details of the implementation of the problems we are solving in this project.

2.1 Data Augmentation

Data augmentation is the process of increasing the amount data ,basically we do not have to collect new data, we have to transform the already present data. As we need more data in deep learning , in some cases it is not feasible to collect data ,so data augmentation comes into picture . It helps to increase the size of data set.

It is done by various image transformation methods:

- Rotation
- Zooming
- Shearing
- Flipping
- Cropping
- Changing the brightness level

In data augmentation phase first all CT scan image are converted into single format (.jpeg) and resized it according to what transfer learning based model required and then normalized in $[0,1]$ so that uniformity will maintain.

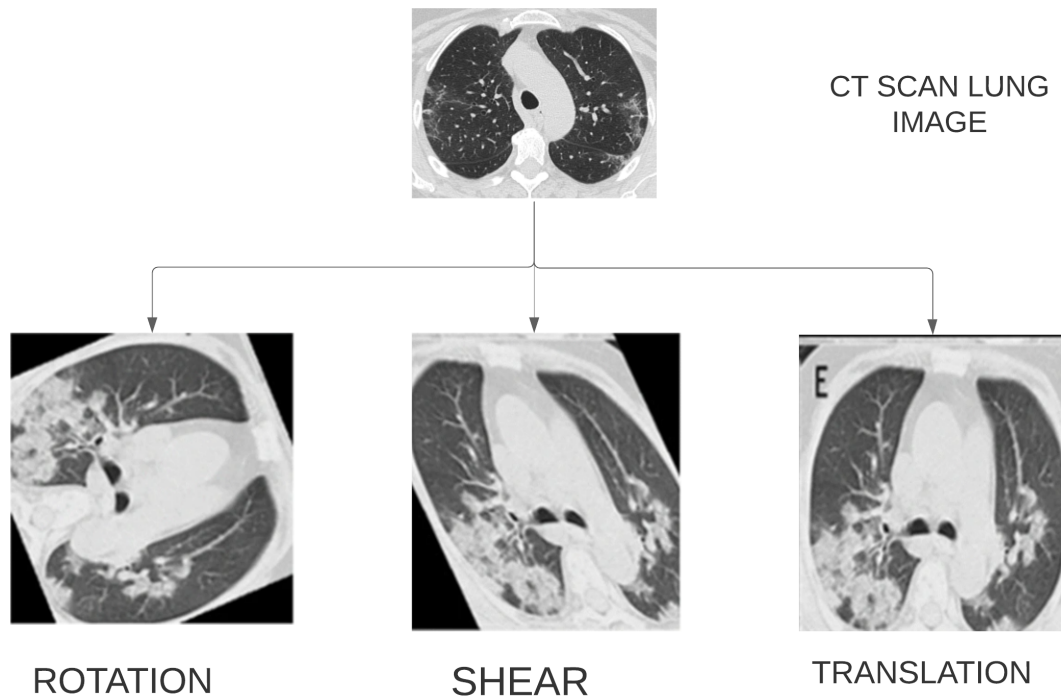


Figure 2.1: Augmented image after Rotation ,Shear and Translation

Here a CT scan image is taken after normalization, various image transformation like Rotation , shear and Translation operation is performed . so that increase in the amount of data set.

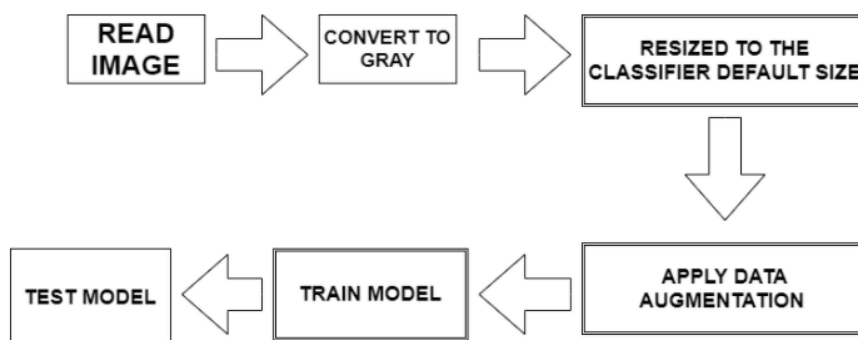


Figure 2.2: Working of Model

Here we Collect the data then normalize it after that convert into gray scale then augment (increase) the data after that we divide the data set into testing and training data set in which 15 percent of data are kept for testing the mode and remaining data are trained on different transfer learning based models . These models are basically used in image classification techniques. These transfer learning learning will classify a given CT scan lung image as COVID Positive or COVID Negative .

After augmentation of data , detection of COVID 19 is done by various transfer learning based model .

2.2 Transfer Learning Model

Transfer learning refers to reusing the learned knowledge from one task and apply it to other task. It is used in classification problem also gives the result fastly.

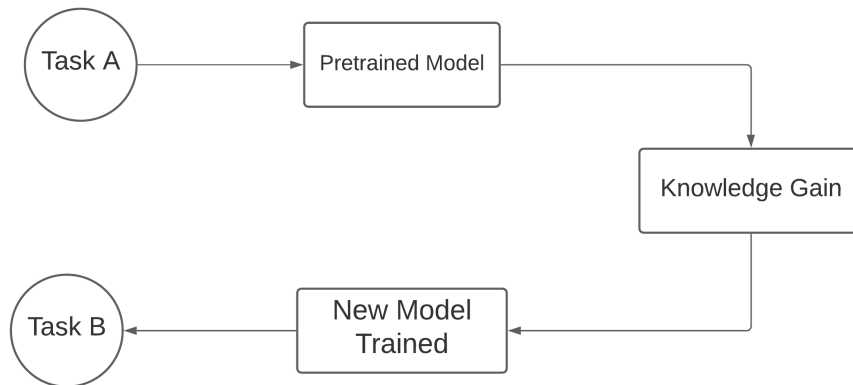


Figure 2.3: Transfer Learning Block Diagram

Here what knowledge that model learned on Task A to train that apply it on task B that is why this Pre-trained model.

There are various Transfer Learning model Like:

- InceptionV3 based Architecture
- VGG16 based Architecture
- ResNet50 based Architecture
- DenseNet based Architecture

2.2.1 InceptionV3 based Architecture

In the InceptionV3 architecture 3×3 convolution is used that decreases the computational time and increase the performance of architecture . Here it deals with the problem where the variation in classification of image is very high and solve these problem by containing different type of kernel in the same level which basically widen the network.

2.2.2 VGG 16 based Architecture

In the VGG (Visual Geometry Group) 16 Architecture having input size dimension of (256*256*3) .In which first two layer having 64 channel of (3*3) filter size and same padding is used after that max polling is applied. The main idea here is to increase the of CNN architecture and replace large kernels with smaller multiple kernels which results more accurate performance.

2.2.3 ResNet50 based Architecture

In this ResNet architecture , stacking of convolutional layer and Polling layer one of the other is done that causes the network performance low due to gradient becomes zero or too large , so to deal with problem connection is used which can basically skip or more layer .The idea of using skip connection is to reduce the training and testing error and reduce overfitting .

2.2.4 DenseNet based Architecture

The DenseNet architecture is the extension of Resnet network it reform on Resnet network by adding dense connection which connects each layer to every other layer . This kind of densely connected layer reflects that each layer get the feature map from preceding layer and pass its feature map to next subsequent layer . Another advantage of using this architecture it to reuse feature while maintaining a low number of parameter in total. There are multiple variety of DenseNet are used among which DenseNet 121 and DenseNet 201 is used in this research paper.

These different architecture based transfer learning models are applied to COVID 19 data set that classify a given CT image into COVID +ve and COVID -ve ,that helps in COVID 19 detection . It may happen that their result will not same while image data fed into these architecture based transfer learning models then Decision fusion comes into picture that works on majority voting .

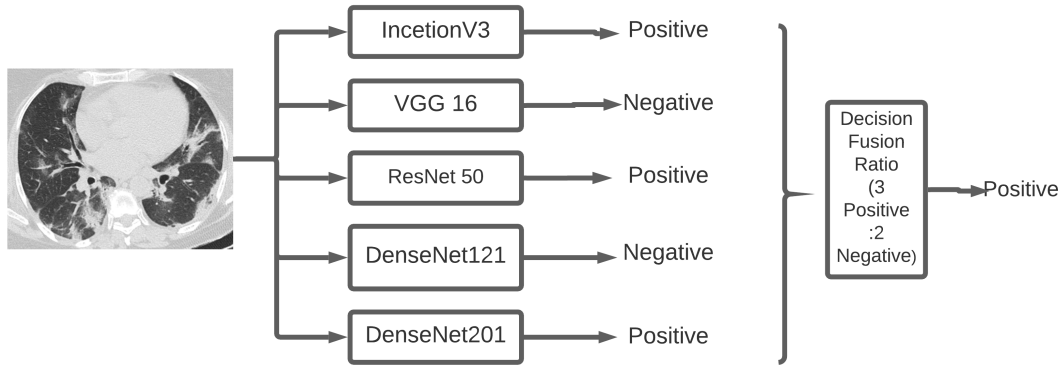


Figure 2.4: Example of Decision Fusion

Here, when a image is passed it into these transfer learning based models then their output having three positive and two Negative After that Decision fusion model that works on majority voting so their final result is positive .

2.3 Implementation Details

In this section we summarised our code step by step.

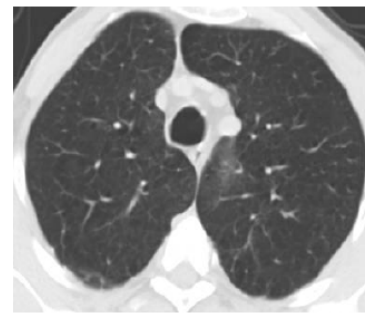
Data pre-processing - First take CT scan image then resized it according to what transfer learning required.

$$I_{normalized} = \frac{I_{Original} - I_{Min}}{I_{Max} - I_{Min}},$$

Then normalized it in the interval [0,1] so that variation will not occur



Non-Covid Lung Image



Covid Lung Image

Figure 2.5: Covid and Non-Covid image

Data Augmentation - As we have limited number of data set available for research purpose, so we have to increase the data set by various transformation mechanism like

random rotation, shear and translation etc.

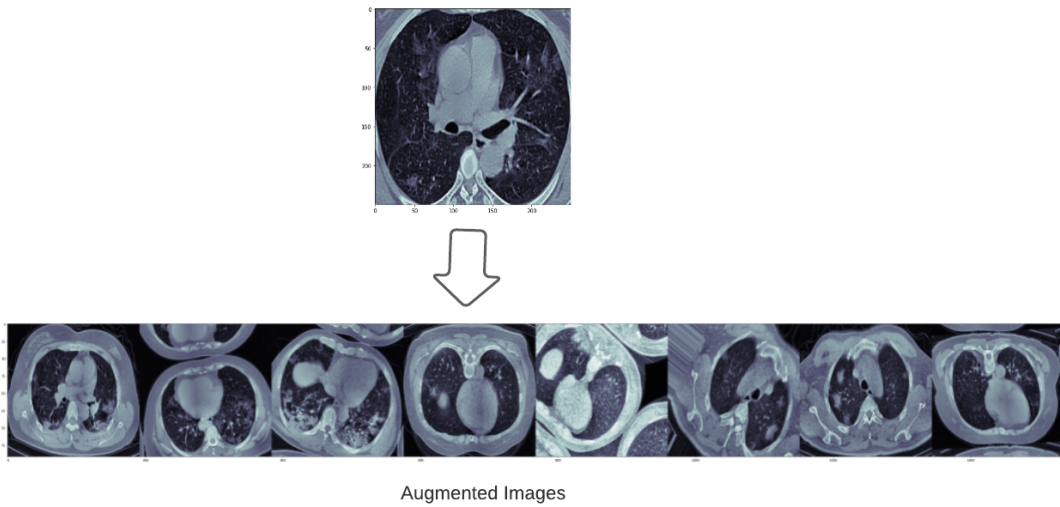


Figure 2.6: Augmented image

COVID 19 Detection - After augmentation of data , various transfer learning based architecture is used to train the model . All these architecture requires input size of image $224 \times 224 \times 3$. Model is applied adam optimizer with learning rate $1e-1$ of batch size 16 . Model is trained upto 50 epochs .Then after decision fusion model are applied which works on majority voting in which final result will be maximum number of outcomes among these model.

Segmentation of Infected region- After classification of CT image into COVID +VE and COVID -VE , segment those region which get infected through virus

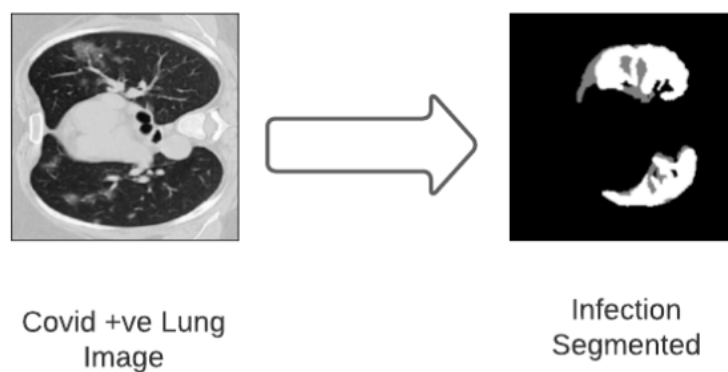


Figure 2.7: Segmentation of infected region

Flow chart of proposed method:

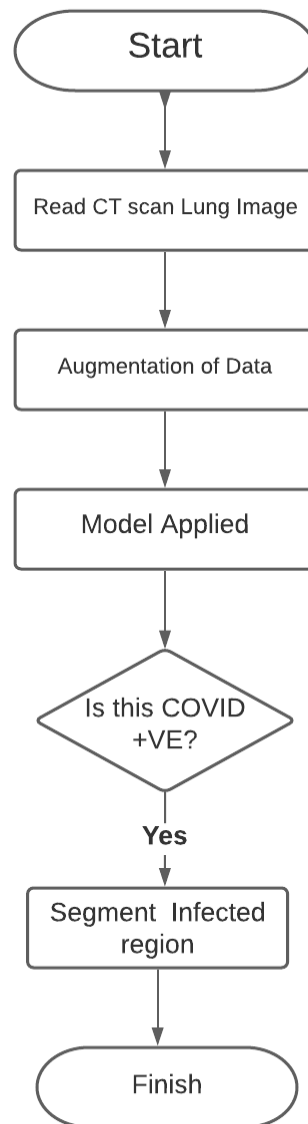


Figure 2.8: Flow chart of method

CHAPTER 3

Result and Discussion

3.1 Result

In this Project firstly i have taken SARS-CoV-2 CT scan dataset from kaggle website .The dataset contains CT scan Lung images in COVID positive and covid negative folder in which 1252 covid positive lung image and 1229 covid negative respectively CT scan lung image . All the images are converted in single format(.jpeg) and and resized according to transfer learning based model then normalize the image matrix in [0,1] so that more variation does not occur . After normalization , data augmentation is done by various operations like translation ,shear rotation etc because we don't have a large dataset . After augmentation , we divide the dataset into testing and training dataset in which 15 percent of data are kept for testing the mode and remaining data are trained on different transfer learning based models . These models are basically used in image classification techniques.These transfer learning learning will classify a given CT scan lung image as COVID Positive or COVID Negative . After applying all these transfer learning based architecture individually then got an average accuracy of 86 percent ,after using decision fusion which basically works on majority voting principle we got the accuracy of 95.32 percent and their confusion matrix are:

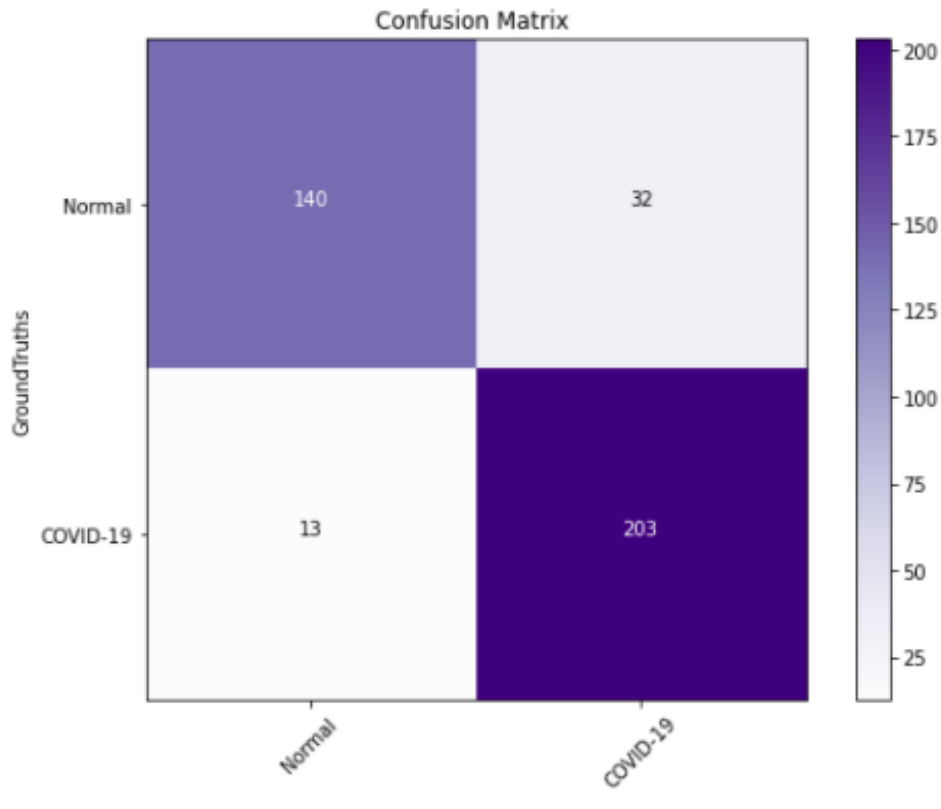


Figure 3.1: Confusion Matrix

Basically we have 15 percent of dataset are kept of testing set in which confusion results shows that :

Confusion matrix - It is better way to evaluate the performance of model .The general idea here is to count the number of times the model predicts true or false value.

- Wrong prediction done by model is categories as:
 - False Positive
 - False Negative
- Correct prediction done by model is categories as:
 - False Positive
 - False Negative

Basically we have 15 percent of dataset are kept of testing set in which confusion results shows that :

- TRUE POSITIVE = 140
- TRUE NEGATIVE = 203

- FALSE POSITIVE = 13
- FALSE NEGATIVE = 32

From the confusion matrix data we calculated accuracy, F1 Score ,precision and Recall . Based on these parameters , comparisons are done on various models .The formula for these measurement are as follows:

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

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

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

$$F1 = \frac{2 \cdot precision \cdot recall}{precision + recall}$$

After calculating these measurement value that shown in table:

Table 3.1: Model Performance.

Model Performance	
Measurement	Value
Accuracy	0.88
Precision	0.91
Recall	0.81
F1	0.85

Now we see accuracy and loss graph at different epochs below. In loss graph as epochs increases their loss decreases it means that there is very less chance to make wrong decision.

In Accuracy graph shows as epochs increases their accuracy increases ,it means that model trained very well.

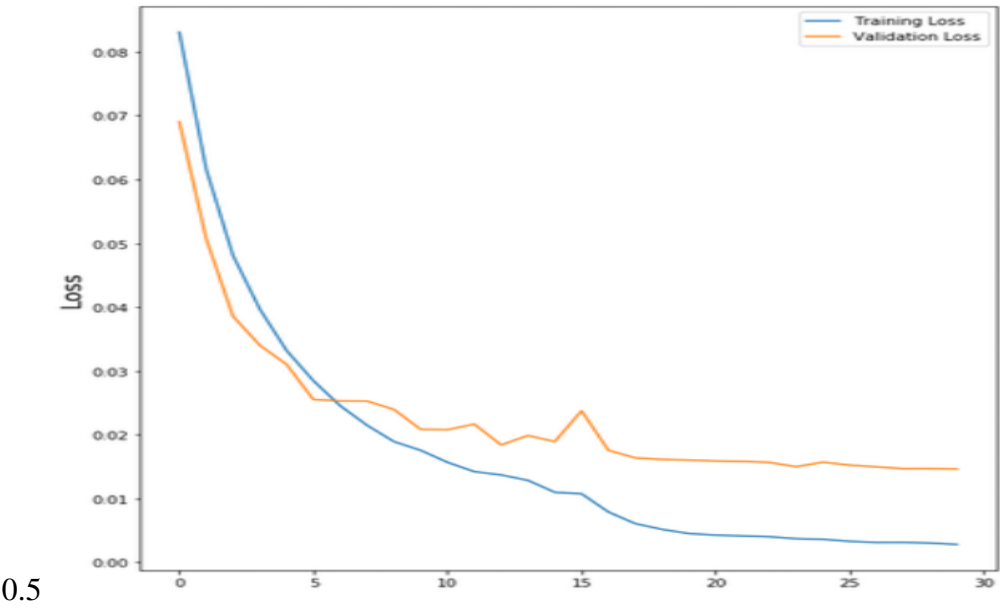


Figure 3.2: Training loss and Validation loss at epochs

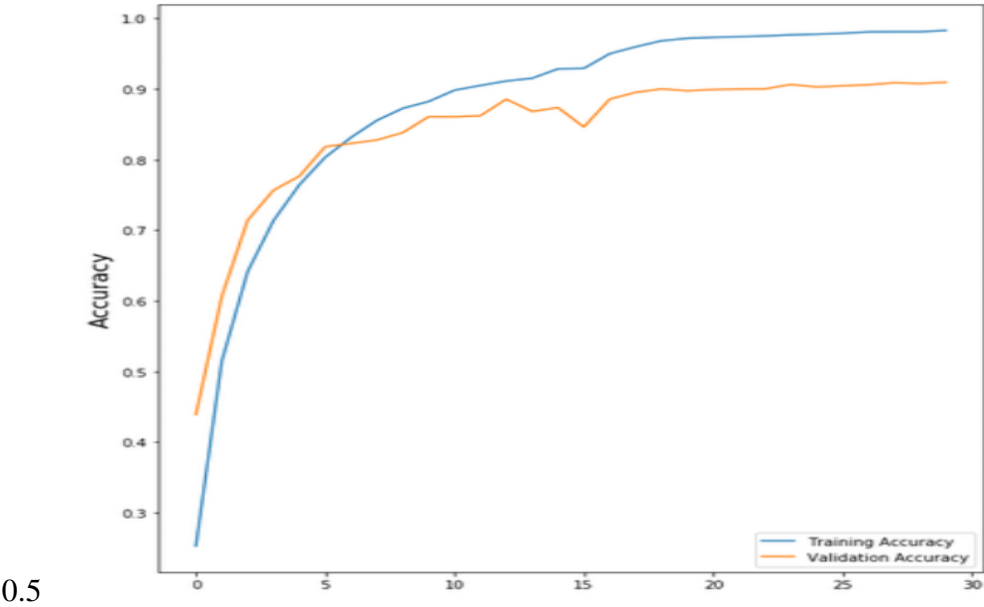


Figure 3.3: Training accuracy and validation accuracy at different epochs

These loss and accuracy are summarised in this table .

Table 3.2: Training accuracy and validation accuracy at different epochs.

Model Performance				
epochs	Training loss	validation loss	Training Accuracy	validation Accuracy
1	0.9808	0.5584	0.6470	0.8112
2	0.6942	0.5119	0.7935	0.811
3	0.6359	0.4289	0.8269	0.8768
4	0.5324	0.3897	0.8585	0.9026
5	0.5236	0.3984	0.8602	0.8954
6	0.4894	0.3786	0.8740	0.9063
7	0.4503	0.3744	0.8836	0.9070
8	0.4206	0.3809	0.8962	0.9036
9	0.4288	0.3377	0.8916	0.9293
10	0.4231	0.3505	0.8934	0.9206

CHAPTER 4

Conclusion and Future Scope

4.1 Conclusion

Deep Learning based classification can help for rapid detection of COVID 19 and other infectious disease .The model In this proposed research paper an experimental evaluation of pretrained deep convolutional neural network , image classification approach is presented to identify COVID 19 detection from CT scan lung image . Moreover, in this research paper , a decision fusion based approach which works on majority voting . It combines all the individual result from transfer learning based models in order to improve the performance accuracy.

From experiment it is showed that decision fusion model achieve better accuracy than individual model. This model having above 86% accuracy and also having low false negative rate . The model are that is trained is very cost effective and user friendly and also can be used in clinic for diagnosis of patient . From experimental observation it is clear that Deep CNN based approach can have a huge impact on the spread of COVID 19 detection also provide past screening . Note that this proposed model is only able to detect the objects with low intensity contrast between infections and normal tissues.

4.2 Limitation

One of the main drawbacks of our project is the lack of data availability for research purpose . The presently available data is very limited to obtain good performance and to replace the thermal imaging technique.

4.3 Future Scope

In this research work only axial image slices of CT image are used . It may provide good result when other section image will be used also with the availability of CT image

with labeled information other lung disease will provide good result.

Also in future ,with the availability of more data,the efficiency of model can be increased

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