Deep Learning Based Covid-19 Diagnosis Using Lung Images

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DEEP LEARNING BASED COVID-19 DIAGNOSIS USING LUNG IMAGES

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Abstract: In 2019, a new virus named corona virus had changed the life of every individual in the world. As the number of covid positive cases had been increased, it causes a very big pressure in the medical field. To overcome this situation, we are in need of some algorithm which predicts whether the person is affected by COVID-19 or not. The most known deep learning method is used to detect whether the person's lung is affected by covid or not. In this project, lung CT images are segmented and then it is given into the simple convolutional neural network. The image segmentation techniques followed are canny edge detection, thresholding technique and U-Net algorithm. From these techniques the better one is chosen and its result is pushed into the convolutional neural network. By segmenting the image and then predicting whether the lung is affected by covid or not increases the accuracy rate and the accuracy value is 95%.

Keywords: Corona virus, Image Segmentation, Deep learning, Convolutional Neural Network

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1 Introduction

The Corona Virus pandemic has caused a great threat all over the world. Most common symptoms are fever, cold, cough, loss of taste and smell. Covid impacts the lungs and damages the alveoli (tiny air sacs). These air sacs helps us to breath easily without any hindrance. If these air sacs are occupied by the corona virus, then it leads to difficulty in breathing and it is the critical stage because oxygen can not be supplied to any of the organs in our body. Lung CT (Computed Tomography) scans can be used for the diagnosis of covid in individuals. Due to the rapid spread of this disease, there is lot and lot of pressure, work and confusion to doctors. So it is a need to develop an algorithm to detect covid in the lung CT image. As an automatic detection tool Deep learning is used recently to find whether the person is affected by covid or not in a faster and accurate way[22]. The main advantage of deep learning over machine learning is that it has its own capacity to execute feature engineering on its own. Deep learning model learns the features by its own while in machine learning the features has to be extracted manually and feed into the model. Deep learning uses Convolutional Neural Network where the input is given as an image which is taken as pixels in machine and it assigns importance to various features in the image. From the recent days research it has been proven that it is well applicable for medical images too. The diagnosis of medical images such as X-Ray, CT and MRI scan can be done using deep learning models. This algorithm is a better suited one to detect any risk in the medical image. From the literature, it is observed that, a deep learning model needs the knowledge of domain experts to train and test the huge amount of data. The alternative for this is to fine tune the training data. Fine tuning sometimes outperforms full training when limited amount of data is available [1].
In case of large amount of data, overfitting is one of the problems. Overfitting is eliminated by using small sized kernels. Pre-processing steps include bias field correction, intensity and patch normalization [2].In few of the research works, DRENet and Resnet are used for preprocessing to overcome overfitting issues. Feature Pyramid Network converts the image into many sub images to predict whether it is covid, pneumonia or normal. This method is efficient only for real images [3]. Assigning the weights manually may not be correct or it may take a high number of trials. So weights have to be assigned automatically. Evolutionary method is to assign weights to each node present in it. The mean classification error rate achieved by EvoCNN is better compared to other methods [4]. Artificial Intelligence uses Alexnet and ResNet-50.In this work, 3D images are sliced axially into 2D images. 96% accuracy rate is achieved [5]. 3D DCNN requires a good architecture and it also requires considerable number of parameters. It is very difficult to design. So it is designed from the 2D deep convolutional neural network. This achieves less computation and processing time [6]. For the process of image segmentation, various techniques have been introduced. SED (Structured Edge Detector) is a segmentation approach used to detect lungs from the chest X-Ray. UCM (Ultrametric Contour Map) and MWT (Marker Controlled Watershed Transform) are used to segment the lungs. These methods are mainly used for large amount of data [7]. After the process of lung image segmentation, the segmented dataset is fed into the training network called patch-based architecture. The lung is divided into patches and the result is appeared from consolidating the patches. This algorithm is used to find whether the lungs is healthy or it is suffering from any disease [8].A rapid, accurate and machinebased segmentation is done. There is good relation between accuracy and complexity maintained here. This makes the model more time efficient and accurate [9].

Generally, physicians used to spot the affected region. To prevent this, CNN with parallel attention module (PAM-Densenet) is used to locate the affected region automatically. Thus, this model learns without any human intervention [10]. Due to the spread of corona virus, deep learning methods are used to find whether the lung is affected by covid or pneumonia. By using CNN model in deep learning, overlapping is eliminated and accurate result has been generated due to the usage of many layers. No segmentation is done, the dataset is directly given to the network for the process [11]. Covid affected region is segmented in 3D chest CT using the method of federated and semi-supervised learning. Non-covid dataset also helps to find the covid affected region through false alarm rejection [12]. Xing Wu proposed that image segmentation is done before passing the dataset to the convolutional neural network. The mask is predicted and it is added with the original CT scan and then given to the network [13].

In this paper, the lung CT images are first segmented using three methods such as canny edge detector, thresholding and U-Net architecture. The segmented results from the best image segmentation technique is selected and it is given into the convolutional neural network. Then the it trains and predicts whether the lung is affected by covid or not.

2 Proposed methodology

The packages which are needed to implement the program are imported. Then the training and testing data are splitted automatically by feeding the test size manually. Here the right and left lung alone is segmented from the original lung CT scans. For the segmentation lung CT images, U-net architecture is used. Fig 1 shows the structural outline.

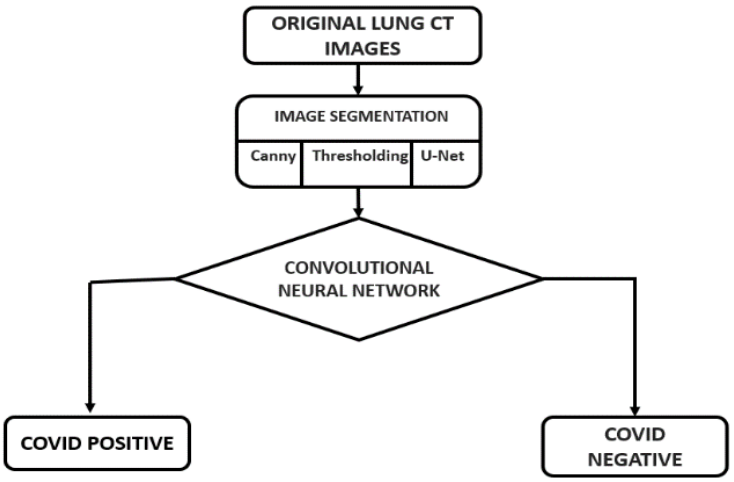


Fig 1 Proposed Methodology

Image segmentation is done using various methods to check which method gives high accuracy. Image segmentation techniques used here are thresholding, canny edge detection and U-Net architecture. In thresholding process, a threshold value is fixed. If the pixel value is greater or lesser than the threshold value, then it is assigned as 255 or 0respectively (Here the pixel value ranges from 0 to 255).

$$g(x, y) = \begin{cases} 1, & \text{if } f(x, y) > T \\ 0, & \text{if } f(x, y) <= T \end{cases} \qquad (1)$$

where g(x, y) is the new pixel value

f(x, y) is the previous pixel value

T is the fixed threshold value

In canny edge detection, the edges are alone detected[21]. Covid CT and its corresponding mask dataset are imported from the google drive. The original images and its masks are sorted respectively. Training and testing data are splitted automatically in the ratio of 70:30 (70 percentage for training and 30 percentage for testing). This architecture looks like U shape so it is called as U-Net and it is shown in Fig 2.U-Net architecture has three parts. The first part is Contracting or Down sampling path, the second part is bottleneck and the third part is expanding or up sampling path. The down sampling path consists of two blocks. In each block, there are two 3x3 convolution layer with same padding followed by a ReLU activation function, a 2x2 max pooling layer and a drop out layer. The bottleneck which is also called as skip connection consists of a single block which consists of two 3x3 convolution layer with same padding followed by ReLU activation layer. It is the connecting path between down sampling to up sampling.

Up sampling layer consists of two blocks. Each individual block consists of one 2x2 convolutional transpose with 2x2 stride and same padding, a concatenate layer, a drop out layer and two 3x3 convolution layer(2D) with same padding followed by ReLU activation function. The up sampling layer is followed by a output layer which consists 1x1 convolution layer(2D) and sigmoid activation function. The optimizer used is Adam Optimizer, Binary cross entropy is used and the metrics used is accuracy. The Call backs function used are early stopping, model checkpoint and reduceLROnPlateau. Next the model is trained and the neural network is saved to a file. If the accuracy is improved the neural network is updated otherwise the neural network remains the same. Certain images are tested.Using this Neural network, the original Lung CT images alone is given as input and the segmented images are stored in two folders namely Covid and Non-Covid. From these three image segmentation techniques, U-Net architecture outperforms canny edge detector and thresholding process. So the segmented images of U-Net are used for further process. Convolutional Neural Network can be seen in Fig 3. 70 percentage is used for Training and 30 percentage is left for Testing. The Convolutional Neural Network designed here is in Sequential manner. Here four 2x2 Convolutional layer, three Max pooling Layer, four Dropout layer, two Dense layer and one Flatten layer. Each Convolutional layer is followed by a ReLU activation function and the output layer consist of Sigmoid activation function.

The convolution formula is:

$$(f*g)(t) = \int f(T)\, g(t-T)\, dT \qquad \text{--------(2)}$$

Mathematically, ReLU is described as,

$$y=\max(0,x) \qquad \text{----------(3)}$$

At last, the sigmoid activation function is used.

$$S(x) = \frac{1}{1+\exp(-x)} \qquad \text{----------(4)}$$

The optimizer used is Adam optimizer and accuracy metrics is followed. The kernel size used is 3x3 and the filter size gets variedfrom one layer to another layer. Padding can also be done. Padding is mainly done to prevent the edge information loss. Stride refers to the number which the kernel should move in both horizontal and vertical direction. Number of epochs can be decided manually. Accuracy rate can be increased by increasing the epoch's number.

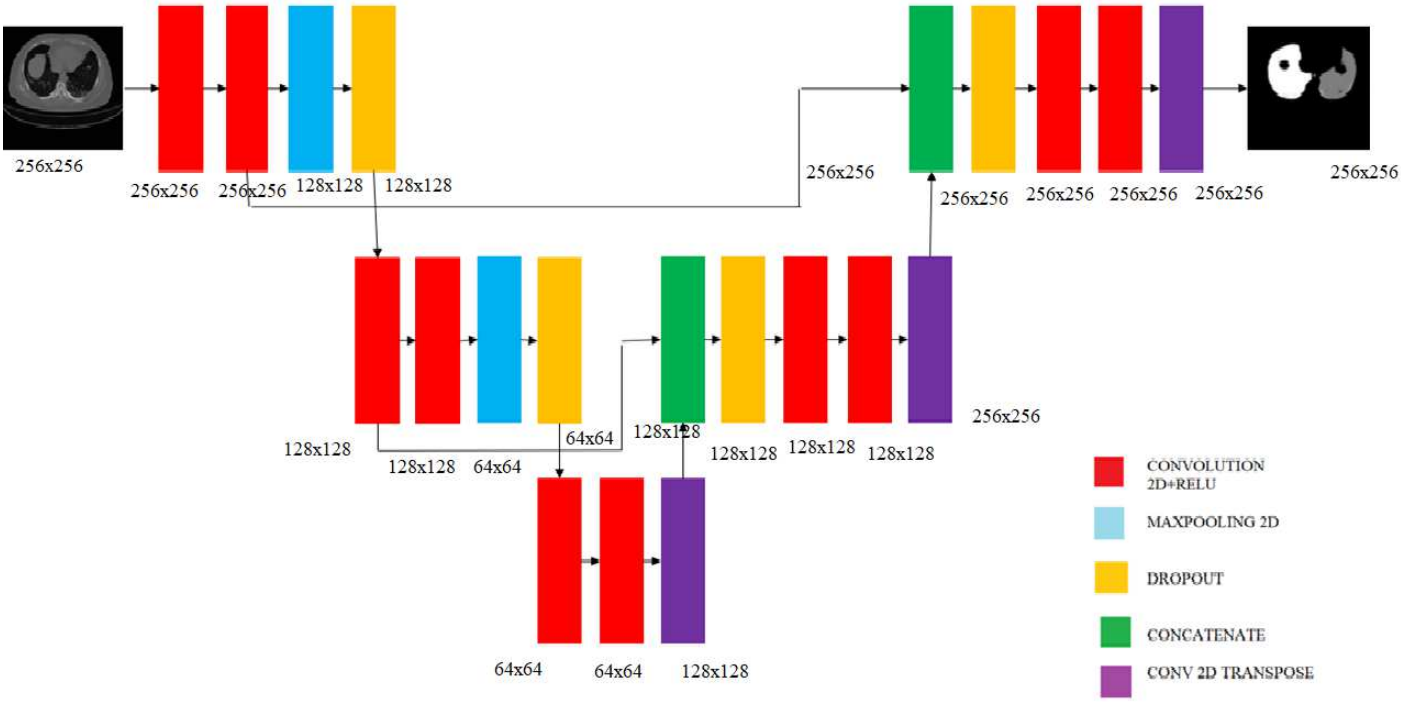


Fig 2 U-Net architecture

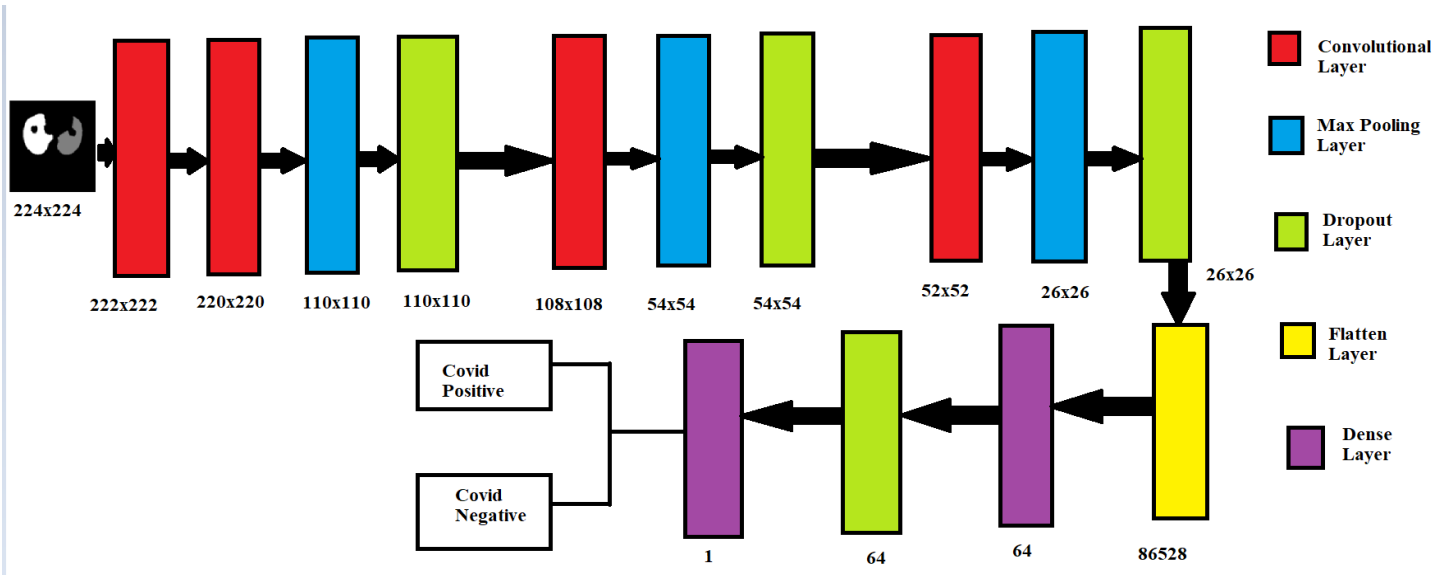


Fig 3 Convolutional Neural Network

3

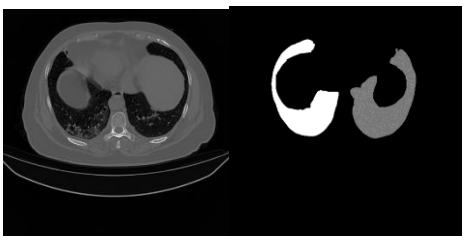
Training takes some amount of time to train the model. For the process of testing a single image is given as input and the result is checked. If the predicted value is less than 0.1 then the Lung is affected by Covid and if the predicted value is above 0.1 then the Lung is healthy.

3 Results and Discussions

The dataset is collected from Kaggle. The total number of images and masks used is 1834. The lung CT image and its corresponding mask is shown in Fig 4.The platform used to work is Google Colab. IOU (Intersection Over Union) metric had been calculated for the three image segmentation techniques. Intersection Over Union is the ratio of area of intersection to the union.

$$IOU = A_i / A_u \qquad \text{----------(5)}$$

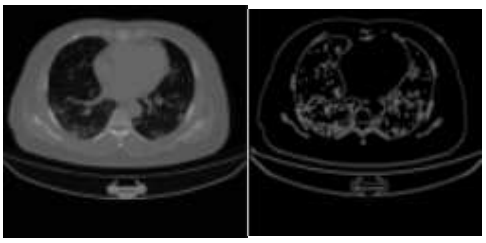
where A_i is the area of intersection
A_u is the area of union



Lung CT image Mask

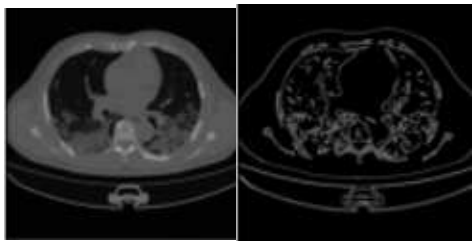
Fig 4

The inputsare given and the command used is cv2.canny(image). After compilation and execution of the program, the edges in the image are segmented. The segmented image obtained from canny edge detection method is shown in Fig 5 (a) and Fig 5 (b).



Lung CT image Canny Output

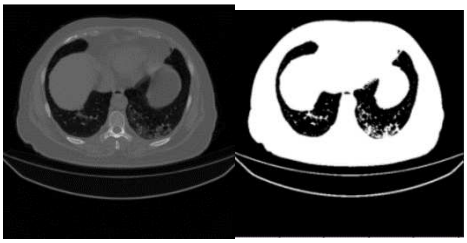
Fig 5 (a)



Lung CT image Canny output

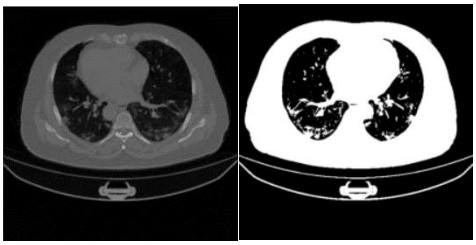
Fig 5 (b)

The pixel value in the image varies from 0 to 255. Here the threshold value set is 150. If the pixel value is greater than 150 then that pixel value is replaced by 255 and similarly if the pixel value is lesser than 150 then that pixel value is reassigned to 0. The following image Fig 6(a) and Fig 6 (b) shows the segmented image using the process of thresholding technique.



Lung CT image Thresholding output

Fig 6 (a)



Lung CT image Thresholding Output

Fig 6 (b)

U-Net architecture needs both the original and mask for segmentation process. The needed libraries are imported. CT images and masks are sorted in order to map the images with its corresponding masks. Images and the size of the filters are given as input into the U-Net algorithm. Epochs used for both training and validation is 20. After the process of training, individual images or a group of images can be tested. The images segmented using U-Net is shown in Fig 7. It consists of the lung CT image, its own mask and the segmented result. The segmented result almost coincides with the mask. There may be very small variation. But the variations between the lung CT masks and the segmented images can be reduced by increasing the number of epochs. Overfitting means it works very well for the training data and the model does not work well for the testing data. To avoid this problem of overfitting, dropout layer is used.

IOU for canny edge detection, thresholding and U-Net architecture are calculated as 0.0706432, 0.490469 and 0.962402 respectively. Thus it can be inferred that U-Net performs well compared to canny edge detection and thresholding technique.

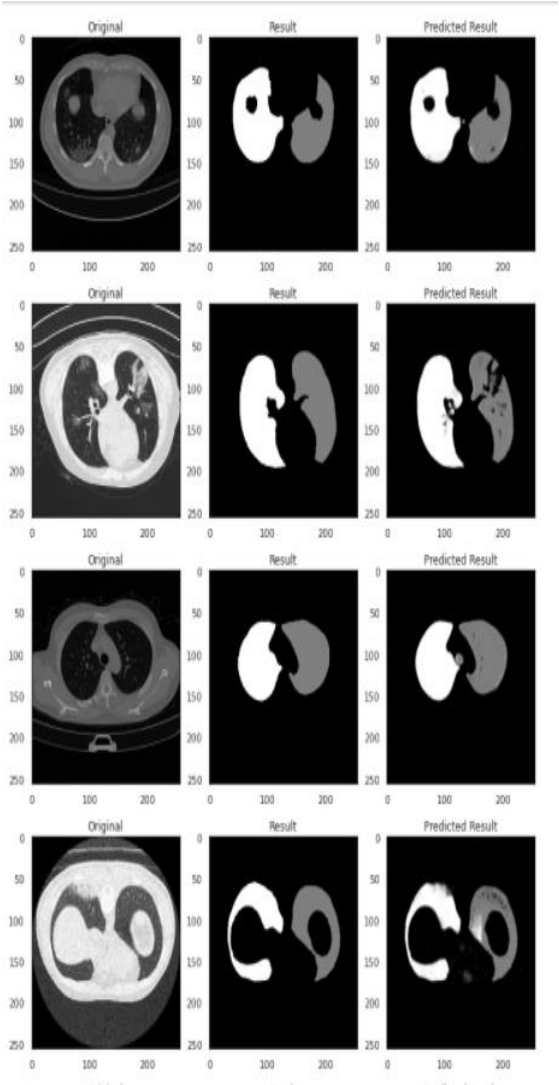


Fig 7 U-Net output

The accuracy obtained by using U-Net architecture is approximately 91 percentage and the following graph is plotted against number of epochs and accuracy in Fig 8. As shown in the figure, the accuracy is increasing when the number of epochs are increasing.

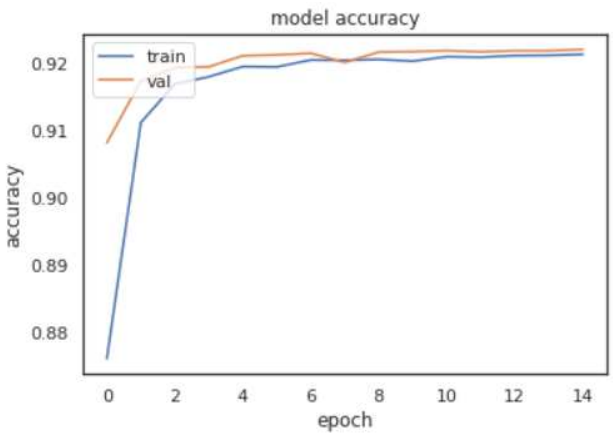


Fig 8Number of Epochs Vs Accuracy

Very less amount of loss is being encountered by using this technique and the graph has been plotted between the number of epochs and loss in Fig 9.

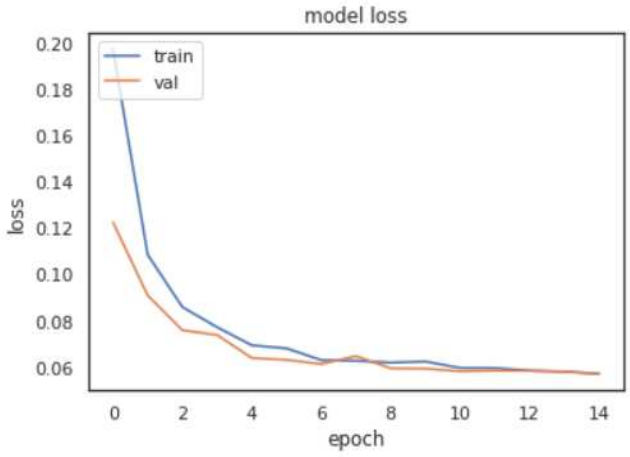


Fig 9 Number of Epochs Vs Loss

When the number of epochs for training is increased, then the model learns more features from the images and it extracts the important features from it. So that it can be able to segment more accurately. Therefore, it is advisable to have more number of epochs.

Performance metrics calculated for U-Net are Precision, Recall, F1-score, Sensitivity, Specificity and Accuracy [20].

Metrics	**U-Net**
Precision	0.8003
Recall	0.9826
F1-score	0.8821
Sensitivity	0.9826
Specificity	0.9760
Accuracy	0.9604

Table 1 U-Net metrics

Table 1 shows the metrics for U-Net architecture. Without image segmentation, the dataset is given as it is into the Convolutional neural network. From this network, the accuracy achieved is approximately 65% and it is shown in Fig 10. Fig 11 visualizes the graph between the number of epochs and loss.

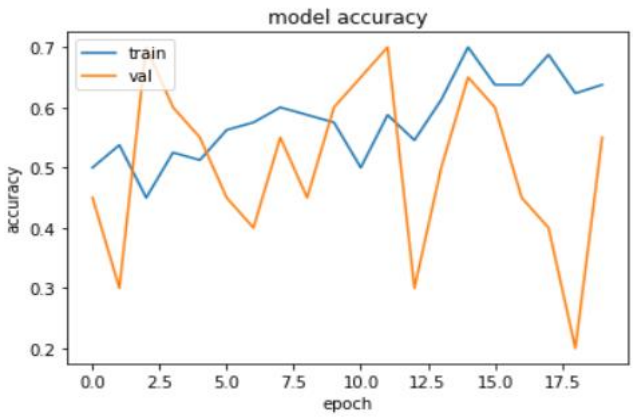


Fig 10 Number of Epochs Vs Accuracy

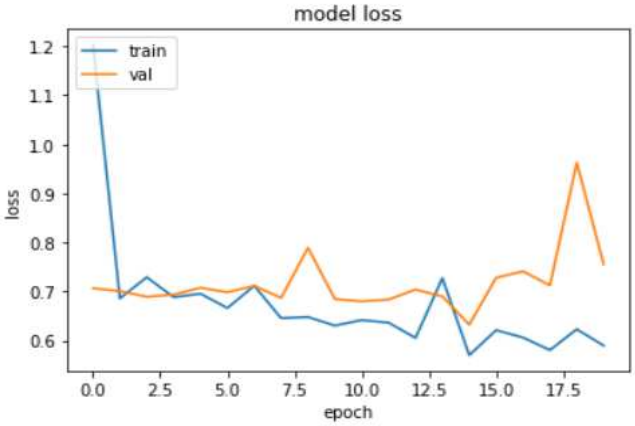


Fig 11 Number of Epochs Vs Loss

The model had been trained for different number of epochs varying from 20 to 500. If a number of 5 epochs is used, then accuracy reached is not of our required level. So the training epochs has to be increased to get a favored accuracy level. After the process of image segmentation, its result is pushed into the convolutional neural network and the accuracy is increased to 92% approximately and the graph between number of epochs and accuracy is shown in Fig 12.

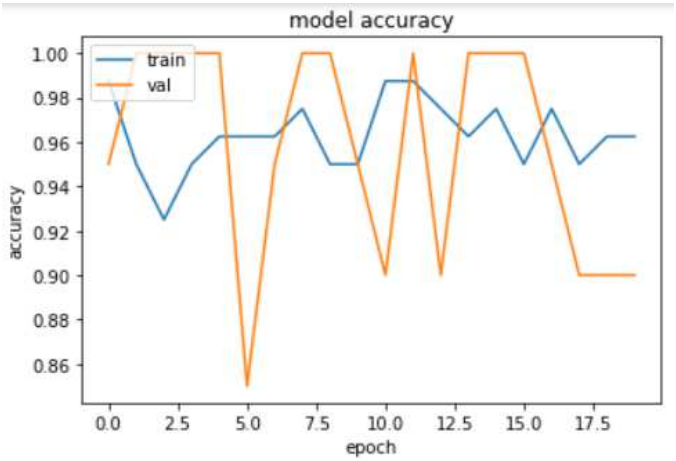


Fig 12 Number of Epochs Vs Accuracy

The following figure (Fig 13) depicts the graph between number of epochs and the loss attained by the model.

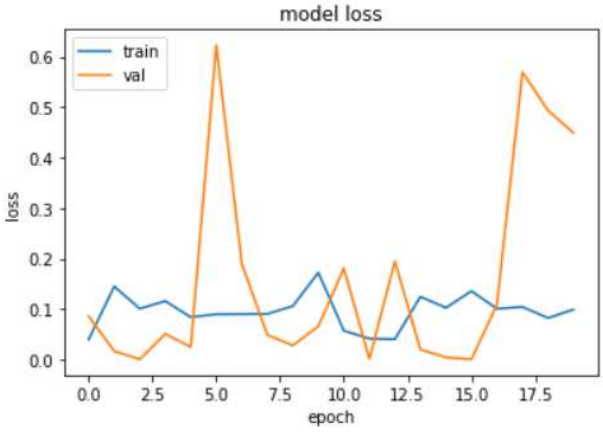


Fig 13 Number of Epochs Vs Loss

The CNN model performs well when the segmented images are passed into it and so the accuracy is increased from 65% to 92 % and the loss is decreased from 50% to 15%.Table 2 shows the training and validation accuracy for Convolutional Neural Network with and without segmentation. The following graph Fig 14 shows the accuracy rate at 20,40,60,80 and 100 epochs.

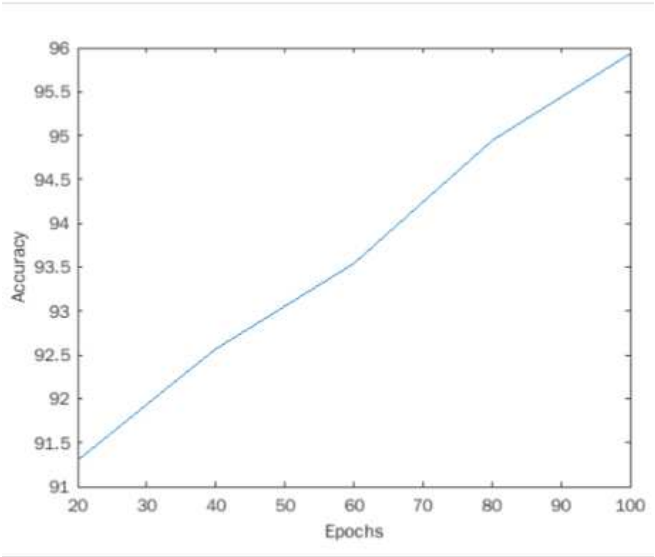


Fig 14 Epochs Vs Accuracy

No. of Epochs	Training Accuracy		Validation Accuracy	
	Without Image Segmentation	With Image Segmentation	Without Image Segmentation	With Image Segmentation
1	0.4625	0.8250	0.60	0.95
2	0.5125	0.8625	0.70	0.75
3	0.6250	0.8750	0.80	0.95
4	0.4805	0.9250	0.50	0.90
5	0.5000	0.9625	0.70	0.95
6	0.5875	0.9000	0.60	0.90
7	0.6125	0.9500	0.60	0.95
8	0.6250	0.9125	0.50	0.95
9	0.6494	0.9375	0.65	0.90
10	0.6250	0.8750	0.60	0.85

Table 2 Training and Validation Accuracy

The analysis of training and testing accuracy is given in Table.2. Different images are passed and tested whether the lung is infected by covid or not. The result is checked for various lung CT images and some of the predicted results are shown in Fig 15.

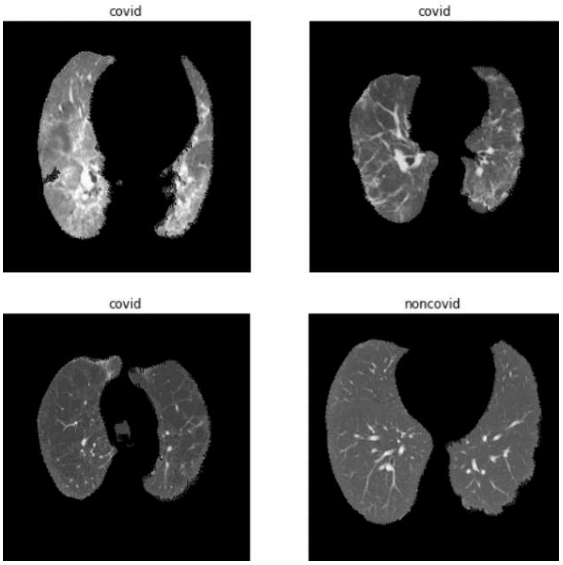


Fig 15 Predicted Results

Our results are compared with some of the existing methods and its accuracy are tabulated in Table 3.

Methods	**Accuracy rate**
Xi Ouyang, et al in 2020 proposed Dual Sampling Attention Network	87.5 %
Hengyuan Kang., et al modelledStructured Latent Multi-View Representation Learning in 2020	95.5 %
Xing Wu., et al in 2020 proposed ResNet-50	95 %
Our Method	95 %

Table 3 Comparison with existing methods

Table 3 describes that when the segmented results of U-Net architecture is given into the ResNet, the accuracy achieved by it is 95 % but the model is somewhat complicated and the training period for it is more compared to the Convolutional Neural Network followed here. Because this CNN takes less time to train and it also achieves the accuracy rate of almost 95 %. In structured latent multi-view representation learning, the accuracy attained is 95.5 % but the model designed for training and testing is very complex. Dual sampling attention network achieved the accuracy rate of 87.5 percentage which is lesser than our current method.

4 Conclusion

The dataset for both covid and non-covid lung CT images were collected. Image Segmentation was performed by using three methods such as Canny Edge Detector, Thresholding and U-Net architecture. Then the comparison between those techniques were done using Intersection Over Union (IOU). IOU value was calculated and it is inferred that U-Net perform well compared to the canny edge detector and thresholding technique. U-Net performs well for lung CT images. The original lung CT images was given into the convolutional neural network without image segmentation. Then the validation accuracy and validation loss attained by it at the end of twenty epochs are 40 percentage and 71 percentage respectively. U-Net results were let into CNN. Here the testing accuracy and the testing loss obtained by it are 95 percentage and 16.54 percentage respectively. So it can be inferred that the accuracy and loss are increased when segmented images are given into the convolutional neural network. Hence this work will be helpful to detect whether the lung is affected by covid or not.

Compliance with Ethical Standards:

Conflict of interest statement:
There is no conflicts between the authors.

Role of funding source:
No funding source

Ethical Approval:
No approval

Informed Consent [if applicable]:
Not applicable

Authors' Contributions:
Author 1: Experimental work, Paper organization
Author 2: Code generation, Experimental work, Paper organization
Author 3: Code generation, Experimental work

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