Segmenting and Classification of Covid-19 in Lung CT Scan Images Using Various Transfer Learning Algorithms and Performance Enhancement by Ensemble Based Approaches

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Abstract. Covid-19 Pandemic has affected India's economy and way of life. Early detection is the key to avoid further spread. For accurate detection of Covid-19 on different imaging modalities, many Deep Learning based image processing algorithms have been proposed. This paper proposes a methodology to detect Covid through CT scans of the Lungs. They are segmented to remove the noise and then classified using various transfer learning-based approaches. U-Net is used for segmenting the CT scans. The ground truths for segmented CT scans required for U-Net were created using Otsu's global thresholding algorithm which produced higher PSNR value of 2.3898 db and lower MSE value of 37800.5621 when compared to other algorithms such as K-Means, Watershed, Fuzzy C Means and local thresholding. U-Net produced 97.50% accuracy. IOU for Covid and Non Covid images were found to be 94.22% and 94.87% respectively. Dice Coefficients for Covid and Non Covid images were found to be 97.02% and 97.37% respectively. These segmented images were given as input to the classification algorithms like Convolution Neural Network (CNN) and transfer learning-based algorithms like VGG-16, VGG -19, DenseNet-169 and DenseNet-201.The accuracies for these models were found to be 85.45%, 88.05%, 88.48%, 94.74%, 98.78% respectively. The DenseNet-201 outperformed all the algorithms. CNN, VGG16, VGG19 showed average performance. In order to make these average learners into strong learners the ensemble models like model averaging, weighted average ensemble, majority voting were considered. The respective accuracies were found to be 91.11%, 91.71% and 89.89%. Weighted Average ensemble performed better than other ensemble-based approaches.

Keywords—CT scan, Covid Detection, segmentation, Otsu thresholding, Transfer Learning, Classification algorithms, Ensemble Ensemble-based approach.

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I. INTRODUCTION

The golden standard test for Covid-19 detection is the RT-PCR.The disadvantage of RT-PCR is that it takes many hours to get the test results. Mardian et al.2021[1] has stated that RT-PCR is prone to false negatives and is reported to occur approximately in the range of 10–40% of patients diagnosed with COVID-19. Another way for detecting Covid19 virus is predicting through Chest X-ray (CXR) images and the CT images. Due to the lack of clinical experts in remote areas, people do not get a chance to meet clinical experts to consult whether the person is actually infected with Covid 19 or not. Human prediction based on seeing CT scans may not be accurate all the time. In order to avoid human errors, AI based models for predicting whether the CT scan is infected with Covid/Non-Covid has become recently popular. These approaches save the time of the people as well as the clinical experts. The challenging part is to develop a model that can increase the true positive predicted rate, so that a proper diagnosis can be made and many people can be cured at the initial stage itself.

II. LITERATURE SURVEY

Literature consists of many deep learning models being applied to the Lung CT scan for detection of Covid-19. Fang et al.2020[2] made a comparative study of sensitivity values of RTPCR and the automated identification of Covid-19 on Lung CT image using Deep Learning algorithms. The sensitivity values of the Chest CT image (50 patients out of 51 patients) were greater than that of the detection rate for RT-PCR (36 patients out of 51 patients). We can conclude that chest CT scan provides high sensitivity when compared with RT-PCR test. Elmehdi et al.2021[3] and Berrimi et al.2021[4] analyzed CT and CXR image and they have stated CT image gives accurate results than CXR images. Pre-processing plays an important role in deep learning algorithms. Kumari et al.2021[5] used K-Means segmentation Algorithm to segment CT scan to remove noise. Satapathy et al.2020[6] segmented the infectious region using Kapur, Otsu and cuckoo search algorithm. They made an analysis and stated that Otsu threshold and ChanVese method gave the best dice coefficient of 92%. Nciri et al.2017[7] segmented the lung nodule using Otsu's global thresholding. Similarly, Rajinikanth et al.2020[8] used the Otsu thresholding method for segmenting infectious regions from the covid CT scan. Oulefki et al.2021[9] proposed a new segmentation algorithm and compared the proposed model with already existing models like Watershed, Medical Image segmentation (MIS) and Graph cut algorithms. Jalal et al.2017 [10] segmented the lung nodule using Fuzzy C means Clustering.

The U-Net is the popular segmentation algorithm that is used for segmenting the biomedical images. Asipong et al. 2021[11] made an analysis with the U-Net Architecture with 4 different scenarios such as original U-Net architecture, 1Layer U-Net, 2Layer U-Net, 3Layer U-Net architecture and stated that original U-Net architecture gave the highest accuracy. Walvekar et al.2021[12] used U-Net architecture for segmentation. The segmentation is carried out in 2 scenarios. One is the lung segmentation and other is the infection segmentation from the Covid CT scan. IOU and Dice Scores were computed for both lung segmentation and the infection segmentation.

Seum et al.2020[13] made an experiment comparing the classification algorithms like DenseNet, ResNet, VGG with two cases. In case one, the CT scan is first segmented and then classified. In the second case the CT scans are directly given to the classification algorithm. DenseNet169 performed best without segmentation. ResNet18 and DenseNet201 performed best with segmentation. So, the researchers stated that segmentation algorithm along with the classification algorithm gives high accuracy when compared with classification algorithm without segmentation algorithm. Foysal et al.2021[14] made an analysis with three CNN models by incorporating different types of layers with the basic convolutional layer and stated CNN model with 3 convolution layers for extracting the features, followed by 3 pooling lawyers for taking the important features and finally with 2 fully connected layers, gives the highest accuracy. James et al.2020 [15] suggested a CNN architecture with 80% of training and 20% testing data that is trained with 75 epochs, gives the highest accuracy. Shah et al.2021 [16] proposed CTnet-10 and compared with other transfer learning approaches like VGG-16, VGG-19, DenseNet-169, ResNet-50, Inception-V3. VGG19 achieved an accuracy of 93.15% which outperformed well than other models. The ensemble models are used for achieving better predictive performance. Prashanth et al.2021[17] proposed UNet one class classifier (OCC) and based on the L2 loss between original and predicted image, they classify whether it is covid or not. Garlapati et al.2021[18] has used Sobel method to segment lesion boundary region from CXR image and classified using support vector machine. Anand et al.2021[19] has proposed a modified VGG deep learning architecture with 200*200 input size to classify whether covid, bacterial, normal, or viral images in CXR image. Yadav et al.2021[20] has used Lung GANs and the extracted features are trained by linear SVC and Random Forest and they are stacked by logistic Regression as a Meta learner. Pillai et al.2021[21] analyzed deep convolutional neural network for detecting covid and normal cases the model gave accuracy of 90%. Verma et al.2022[22] used Otsu's global thresholding for segmenting lung parenchyma to remove the impurities from foreground objects and highlighted the lesion using attention heatmap. Subramanian et al.2022[23] has proposed 3 models like transfer learning and fine tuning on deep CNN, Novel CNN, finally other methods like hierarchical classification, ensemble models etc. Depthwise separable CNN+ Deep Support vector machine gave highest accuracy of 99.06%. Mouhafid et al.2022[24] implemented 2,3 level stacking with model averaging the final predictions and they compared with weighted average ensemble and stated WAE method performed better than stacking method. Chen et al.2021, Beltus et al. 2020 [25][26] these researchers used majority voting method for ensembling the base learners. Wehbe et al.2021[27] used weighted average ensemble method to ensemble several base learners.

III PROPOSED SYSTEM

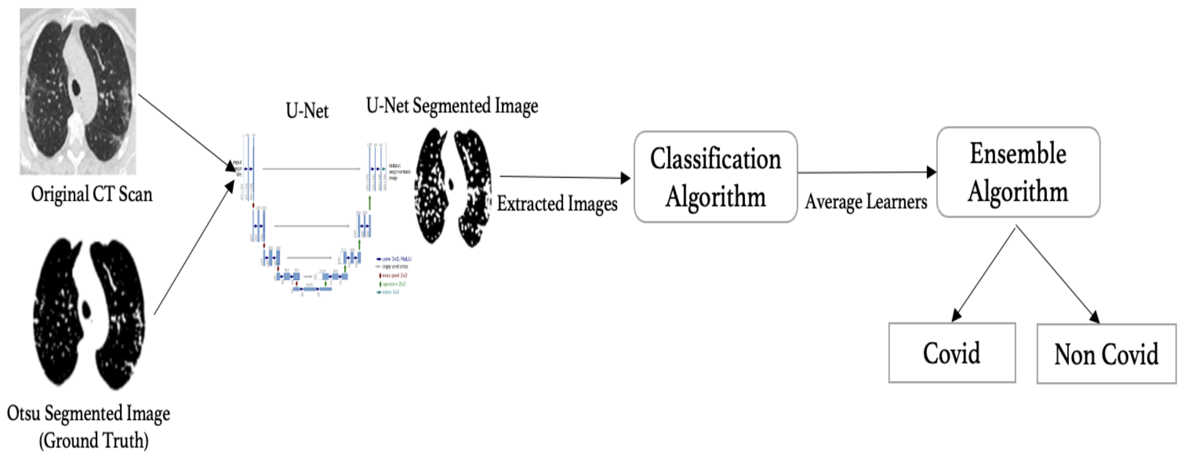


Fig.1. Proposed System Architecture

Proposed Methodology

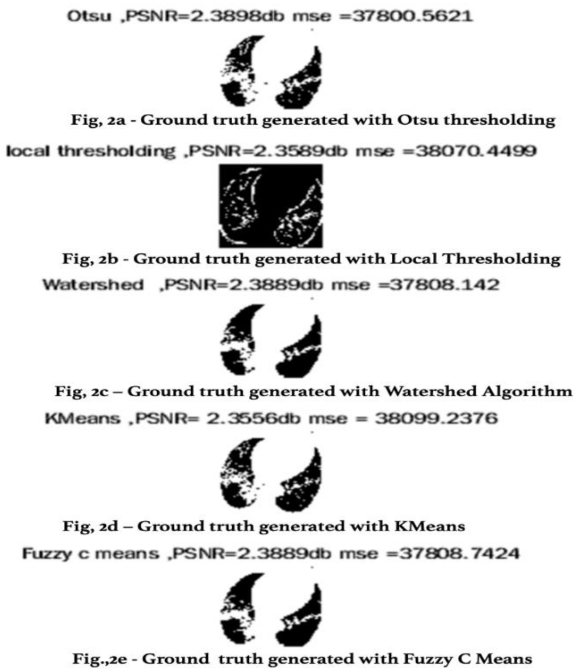
As a preliminary step, the CT scans were segmented using Otsu's global thresholding. This algorithm was chosen as it got the highest PSNR and least MSE values (refer Table 1) when compared with other popular segmentation algorithms like Watershed, KMeans, Fuzzy C means and local thresholding algorithms. The segmented images of Otsu were taken as the ground truth for U-Net segmentation. The U-Net segmented images were then classified using some of the transfer learning-based classification algorithms. Finally, the average learners were ensembled using model averaging, weighted average ensemble and majority voting and the results were compared using standard metrics. Refer Fig.1 for the detailed proposed architecture.

Dataset

The SARS-COV-2 CT Scan dataset is obtained from Kaggle[28]. It has a large dataset of CT scans for Covid-19 identification. This dataset has publicly available CT scans which are taken from Sau Paulo, Brazil. It has 1252 CT scans and 1230 Non-covid CT scans. 80% of CT scans were used for training and remaining 20% were used for testing.

Segmentation

Segmentation plays an important role in diagnosing Covid-19. Seum et al.2020[13] stated segmentation along with the classification gives higher accuracy than classification without segmentation. The main idea behind the segmentation is to remove impurities from the foreground objects so that ROI region is highlighted for accurate prediction. The image segmentation increases the model accuracy. Kumari et al.2021[5] used K-Means as the segmentation algorithm. Satapathy et al.2020[6], Nciri et al.2017[7], Rajinikanth et al.2020[8] and Verma et al.2022[22] used Otsu’s method for segmenting the lung and lesion part. Oulefki et al.2021[9] used watershed algorithm for segmenting lesion region. Jalal et al.2017 [10] segmented the lung nodule using Fuzzy C means Clustering. Several segmentation algorithms like Watershed, KMeans, Fuzzy C means, local thresholding algorithms were compared with the original image using the PSNR and the MSE values. The best performing algorithm was chosen for creating ground truth for U-Net architecture. The best algorithm should have higher PSNR and lower MSE value. The implementation was done in MATLAB. The ground truths generated with various segmentation algorithms are as given in Figure 2.



Fig, 2a - Ground truth generated with Otsu thresholding

Fig, 2b - Ground truth generated with Local Thresholding

Fig, 2c – Ground truth generated with Watershed Algorithm

Fig, 2d – Ground truth generated with KMeans

Fig.,2e - Ground truth generated with Fuzzy C Means

Table 1. PSNR and MSE for Segmentation Algorithms

Algorithms	PSNR	MSE
Otsu's Global thresholding	2.3898 db	37800.5621
Local Thresholding	2.3589 db	38070.4499
Watershed	2.3889 db	37808.142
KMeans	2.3556 db	38099.2376
Fuzzy C Means	2.3889 db	37808.7424

Otsu's global thresholding gave a better PNR and least MSE value among other algorithms (refer Table 1), therefore Otsu's global thresholding was chosen for creating ground truths for the U-Net architecture.

U-Net Segmentation

U-NET architecture was specially created for biomedical segmentation. It has many applications in medical domain. The U-Net architecture has two main parts. One is the contractive path (Encoder) and the other is the expansive path (Decoder). The main aim of this architecture is to link the encoder and decoder path to get high accurate information. Asipong et al. 2021[11] and Walvekar et al.2021[12] used U-Net for segmenting the lesion region. Prashanth et al.2021[17] proposed UNet one class classifier (OCC) and based on the L2 loss between original and predicted image, they classified whether it is Covid or Non-Covid. A sample original CT scan image, the result of Otsu's global thresholding and the corresponding output of the U-Net is shown in Fig. 3.

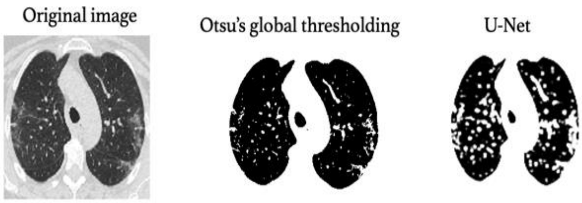


Fig.3. Segmentation Result

Classification Algorithms

The U-Net segmented image is given to some of the transfer learning-based approaches. Seum et al.2020 [13] stated DenseNet201 performed well in classification with segmentation and Densenet169 performed well in classification without segmentation. James et al.2020 [15] stated 80% for training CNN model and 20% for testing gave the highest accuracy. Foysal et al.2021[14] stated CNN with 3 convolution layers, 3 max pooling layers. 2 fully connected layers performed best. Subramanian et al.2022[23] stated Depthwise separable CNN with Deep Support vector machine gave highest accuracy. Shah et al.2021 [16] compared the proposed model CTnet – 10 with other classification algorithms like Inception V3, ResNet-50, VGG-16, VGG-19, DenseNet-169. The top three model that performed well were VGG19, VGG16, DenseNet169. So, we have chosen these Top five algorithms for the next step of classification. We have compared CNN, VGG16, VGG19, DenseNet169 and DenseNet201 models. We have designed the CNN with three convolution layers for extracting the features, and followed by three max pooling layers and finally with 2 fully connected layers. Other transfer learning models like VGG16, VGG19, DenseNet169, DenseNet201 were implemented based on

ImageNet weights. These models are trained with 25 epochs, the learning rate is set as 0. 001.Sigmoid activation function was used in the dense layers and the loss is calculated by categorical cross entropy. Adam optimizer is used for optimization. The accuracies for various Transfer learning-based approaches are listed in Table 3.

Ensemble Models

Based on the performance of the Transfer learning-based approaches, the average performing learners were ensembled to produce a strong learner. Model averaging, weighted average ensemble, majority voting were used to ensemble our average learners. The CNN model, VGG16, VGG19 models were chosen as the average learners as they performed with lesser accuracy compared with other algorithms.

IV. RESULTS

Evaluation Metrics for Segmentation Algorithm

Dice Score: This measure denotes how well the image is segmented. The range of the Dice Coefficient should be between 0 to 1. If the dice coefficient is nearly 1, then it is considered a good score.

Dice Coefficient (A, B) = $\frac{\mathbf{2|A\cap B|}}{\mathbf{|A|+|B|}}$ (1)

Intersection Over Union (IOU): Intersection Over Union is similar to Dice coefficient. They are correlated positively. It is otherwise known as Jaccard index or Jaccard coefficient. The range of IOU should be between 0 to 1. Table 2 lists the Dice Score and the IOU for Covid and Non-Covid categories.

Intersection_Over_Union (A, B) = $\frac{|A\cap B|}{|A\cup B|}$ (2)

Table 2. Dice Score and IOU

Metrics	Dice Score	IOU
Covid	97.02%	94.22%
Non-Covid	97.37%	94.87%

Evaluation Metrics for Classification Algorithm

Accuracy: Once the model is trained, the testing images are used to find the accuracy of our model. The validation accuracy gives the percentage of correct predictions for our Test dataset. Table 3 lists the accuracies of the classification models.

Accuracy = $\frac{\mathbf{(TP+TN)}}{\mathbf{(TP+FP+TN+FN)}}$ (3)

Table 3. Accuracies of Classification Model

Model	Accuracy
CNN	85.45%
VGG16	88.08%
VGG19	88.48%
DenseNet169	94.74%
DenseNet201	98.78%

DenseNet201 has achieved 98.78% accuracy. It performed better than all other models (refer Fig.4). We conclude that DenseNet201 works best for classifying covid or not in our dataset.

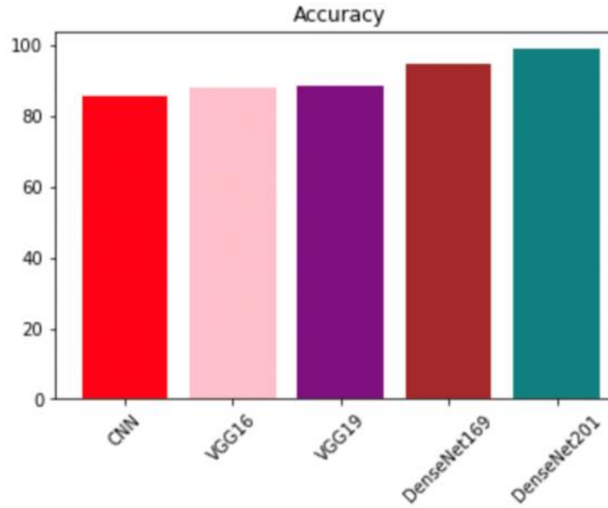


Fig.4. Bar chart based on classification model accuracies

Precision, Recall, F1 Score

Precision is defined as what percentage of data is truly positive among all the positive predicted data. It ranges from 0 to 1. The precision can be calculated by the formula

$$\text{Precision} = \frac{\text{Truepositive}}{\text{Truepositive}+\text{Falsepositive}}$$

Recall is defined as what percentage of data are predicted positive among the total positive data. It is otherwise called as true positive rate (TPR). The value ranges from 0 to 1. The recall can be calculated by the formula

$$\text{Recall} = \frac{\text{Truepositive}}{\text{Truepositive}+\text{Falsenegative}}$$

F1_Score is defined as the Harmonic Mean of the recall value and the precision value. F1_Score uses false negative as well as false positives for calculation. It gives same weightage for precision as well as recall. F1 score gives the overall accuracy for our trained model.

$$\text{F1\_Score} = \frac{2*(\text{precision}*\text{recall})}{(\text{precision}+\text{recall})}$$

Table 4. Evaluating Classification Models

Metrics	Precision	Recall	F1 Score
CNN	0.88	0.85	0.85
VGG 16	0.88	0.88	0.88
VGG19	0.90	0.88	0.88
DenseNet169	0.95	0.95	0.95
DenseNet201	0.99	0.99	0.99

DenseNet201 achieved highest F1 score of 99% for both covid images and non-covid images. Followed by that DenseNet169 gave F1 score of 95%. VGG16 and VGG19 gave same F1 score of 88%. CNN performed the least. (Refer Table.4) for accuracy of each classification model.

Ensemble Algorithms

The average learners like CNN, VGG16, VGG19 are ensembled using several ensemble algorithms

Table 5. Comparison with Ensemble methods

Model	Accuracy
CNN	85.45%
VGG16	88.08%
VGG19	88.48%
Model Averaging	91.11%
Weighted Average Ensemble	91.71%
Majority Voting	89.89%

Table.5 lists the accuracies of the average learners and the accuracies of the ensembled model. Weighted Average ensemble method performs better than all individual average learners and other ensemble methods.

V. CONCLUSION

In this paper, the Lung CT images were first segmented to remove noise and unwanted area. The segmentation is done using U_Net segmentation algorithm. Since we do not have ground truth images in our dataset, we have created ground truth using Otsu's global thresholding method since it got highest PSNR value and lowest MSE value among other algorithms like watershed, k-Means, Fuzzy C Means, local thresholding. The Otsu segmented images were given to U-Net segmentation algorithm. The segmented images were then classified using various Transfer learning-based classification algorithms. DenseNet201 gave the highest accuracy of 98.78%. It out performed well than other algorithms. Followed by it DenseNet169 performed well. It achieved accuracy of 94.74%. VGG16, VGG19 nearly gave same accuracy of 88%. At last CNN gave the accuracy of 85%. The average learners were chosen to improving the accuracy by using Ensemble based approaches. Weighted average ensemble performed better for ensembling the average learners. In future we plan to extend the work by implementing other Ensemble based methods to make average learners to strong learners.

VI. ACKNOWLEDGEMENT

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