COVID-19 Lung Infection Segmentations using Neural Networks based on CT Slices

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Abstract: ***Beginning in early 2020, COVID-19, a health emergency and existential threat to society, began to spread globally. The current healthcare approach to combat COVID-19 has the potential to be considerably improved by automated lung infection detection utilising computed tomography (CT) images. To segment contaminated areas from CT slices, however, there are a number of difficulties, including low intensity and a wide range of infectious features when comparing infected and healthy tissues. Additionally, it is not feasible to collect a big amount of data quickly, which inhibits the deep model from being trained. To overcome these difficulties, a novel COVID-19 Lung Infection Deep Network Segmentation is proposed to autonomously separate unhealthy areas from slices of a chest CT image. This study provides a segmentation technique for Ground Glass Opacity or ROI identification in CT images caused by corona viruses. The area of interest was categorised down to the pixel level using a modified Unet model structure. Instead of the time-consuming RT-PCR test, CT scans can be utilised to diagnose COVID-19. Using this segmentation method, doctors were able to diagnose COVID-19 more quickly, precisely, and consistently.***

Keywords: CT scan, RT-PCR, ROI identification, UNet

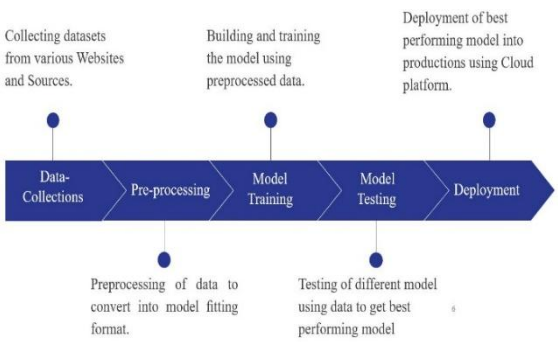
1. Introduction

A health and financial crisis was caused by the Covid-19 (Coronavirus) virus's global spread. It is also highly transmissible and infectious. It also comes in different waves. One cannot anticipate when it will end. The lungs are largely impacted by the second wave of COVID-19, which is brought on by the Delta variation. The present healthcare strategy to reduce COVID-19 has the potential to be considerably improved by automated lung infection diagnosis utilizing computed tomography (CT) images. Many obstacles, such as the vast range of infection features and the diffuse contrast between infected and healthy tissues, make it difficult to separate ill regions from healthy ones in CT slices. The suggested CNN+ Unet-based solution addresses these problems. To mark the issue of enormous data requirements, a semi-supervised technique was then adopted. The proposed Unet-like model enhances the predicted region of interest's receptive field, allowing for the collection of more data and enhancing the model's capacity to identify edges. The performance of the recommended model performs well due to its quantitative results when compared to the fundamental Unet technique and other cutting-edge models. Because CT screening provides advantages over X-rays, such as providing a three-dimensional image of the lung, it is the best technique. According to recent studies, CT slices can reveal infection-related symptoms like Ground Glass Opacity (GGO) in the early stages and lung accumulation in the late stages. It would be beneficial to qualitatively describe COVID-19 and monitor longitudinal changes in CT slices in order to combat the infection successfully. However, manually identifying lung infections requires a significant amount of time and work. Additionally, radiologists' annotation of infections is a highly subjective endeavour that frequently takes into account their own biases and clinical experiences. We suggest a special COVID-19 Lung Infection Segmentation Deep Network (Inf-Net) for CT slices to address the aforementioned problems. [1].When diagnosing a lung infection, medical professionals must first roughly pinpoint the diseased area in order to appropriately extract its contour from the other features. The danger of dying increases with lung infections. Only a small portion of doctors are capable of early detection during a pandemic, which could lower the likelihood of a death.

2. Related Works

The diagnosis of lung issues frequently uses CT imaging. We suggest a new Deep Network (Inf-Net) for COVID-19 Lung Infection Segmentation for CT Slices to address the former problems [1]. Recent performances of numerous compositions have been well welcomed. These methods usually employ an extract feature classifier for nodule segmentation in lung CT. We segment the COVID-19 infection zones into sub regions in our work to track and assess the disease's evolution. Despite being able to discover the anomalous region, the (unsupervised)anomaly detection/ segmentation was unable to determine whether it was connected to COVID-19.The semi-supervised model, which is better suited for evaluating COVID-19 based on the weakly labelled data, could separate the target region from other anomalies. Semi-supervised learning (SSL) seeks to enhance model performance with a big amount of unlabeled data and a small amount of labelled data. The SSL technique is increasingly used for deep neural network training. In order to reduce the loss on the labelled data, these techniques frequently combine a supervised loss applied to the labelled data and an unsupervised loss applied to either the unlabelled data alone or both the labelled and unlabelled data. The use of a cross-entropy loss, which is calculated using the unlabeled data with fictional labels. and is regarded as an additional supervision loss, is therefore advised.

3. Proposed Model Overview



i.Data Collections: The fuel for ML models is data. Data has been acquired from Kaggle using the Kaggle api. Lung segmentation of the chest and an infection mask make up the data set. It is made up of roughly 1600 lung images in.nii (3d ct scan) format. The following pictures are part of the data. Both the infection mask and the lung mask are in distinct pictures.

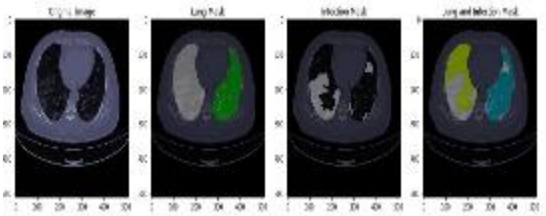


Figure 1: Data Collections

ii. Data Pre-processing: Data must first be converted from the.nii format to jpg before being cropped. CLAHE improved the images after cropping for better feature capture and visualisation. Lungs component from original pictures are then segmented for enhanced feature acquisition,then photos with defined dimensions. After that, analyse the data histogram and convert the photos to grayscale. Finally, there are data enhancements that rotate and flip images to get more accurate and varied data.

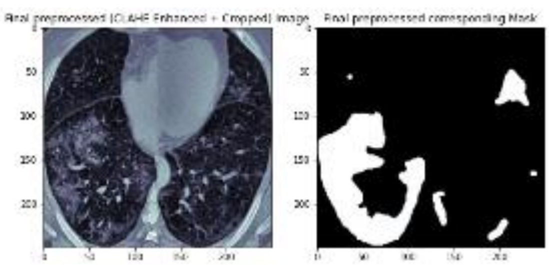


Figure 2: Data Pre-processing

4. Project Implementation Plan

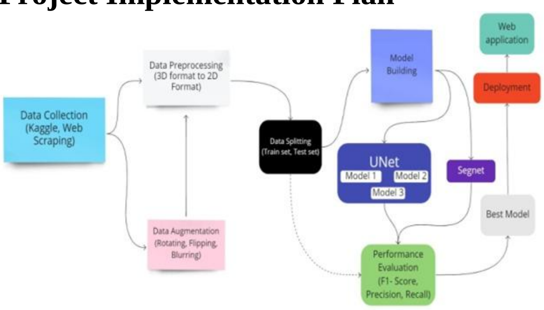


Figure 3: Project Implementation Plan

In this figure, first we collected the dataset from various websites like Kaggle and Web Scraping for implementing this plan. Then it is passed through the Data preprocessing and Data Augmentation block for further processing. In Data Augmentation block we do the Rotating, Flipping and Blurring of 3D image because initially CT scan images are in the form of 3D format. Then it is given to the Data preprocessing block for converting into 3D to 2D format of the image. After the image data converted into the 2D format then Data Splitting is done as divided as training set and testing set. In this case, we split the data in half, using 30% for model testing and 70% for training. Model is constructed using Unet and SegNet models, two cutting-edge models. For SegNet model we used different three iterations named as Model 1, Model 2 and Model 3.Then the models are given to the Performance evaluation for observing F1 score, precision and recall. The best model is found from the performance graph for deployment of the results and pass through the created web application and mobile application platform.

5. Model Architecture

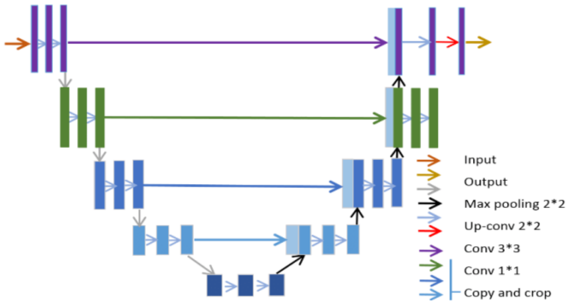


Figure 4: Unet Model

The semantic segmentation architecture is called U-Net. It comprises of an expanded path and a contracting path. The contracting path follows the convolutional network's typical topology. Repeatedly, two 3x3 convolutions are utilised after a 2x2 max-pooling layer and a Rectified linear unit (ReLU) are used for downsampling (unpadded convolutions).The number of feature channels is multiplied by 4 with each downsampling step. Upsampling the feature map is after that two 3x3 convolutions, each followed by a ReLU, at each stage of the expansive path, a 2x2 convolution ("up-convolution") that decreases the number of feature channels in half, and an association with the properly cropped feature map from the contracting path, and two 3x3 convolutions. Since every convolution loses border pixels, cropping is required. Each of the 64 feature vectors' 64 components is mapped to the impulse number of classes via the final layer's 1x1 convolution. There are a total of 23 convolutional layers in the network.

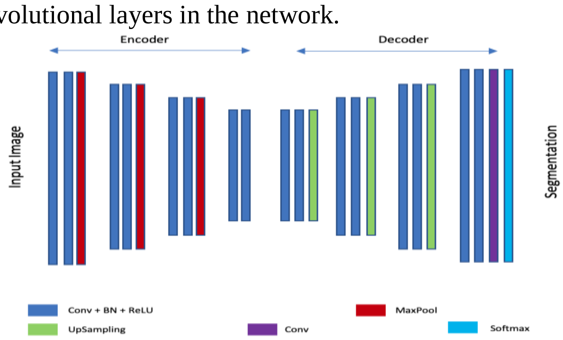


Figure 5: SegNet Model

SegNet is a semantic segmentation model and an encoder network comprise its basic trainable segmentation architecture, a pixel-wise classification layer, and an associated decoder network. The VGG16 network and the encoder network both feature 13 convolutional layers with the same topological structure. The decoder network's job is to convert full input resolution feature maps from low resolution encoder feature maps for pixel-wise classification. Upsampling the lower resolution input feature maps by the decoder is new for SegNet. The matching encoder's max-pooling stage generates pooling indices that the decoder specifically uses to do non-linear up sampling.

6. Algorithm Used

Convolutional Neural Network (CNN)

When given inputs like images, voice, or audio, for example, convolutional neural networks perform better than other types of neural networks. Fundamentally this can be divided as 3 types: Pooling, fully connected and convolutional layer. Generally, in convolutional networks convolution layer is used as the top layer. Convolutional layers, further convolutional layers, or pooling layers might come after the fully connected layer, but they do not make up the final layer. With each layer, CNN gets more resilient and is able to recognise bigger portions of the image. Basic features like colours and borders are highlighted in the early layers. The target item is finally recognised when the visual data advances through the CNN layers, starting with recognition of the object's major characteristics or forms.

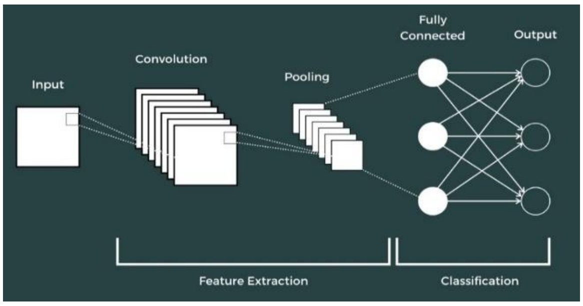


Figure 6: CNN Model

$$p_k(x) = \exp(a_k(x))/(\sum_{k'=1}^{k} \exp(a_{k'}(x)))$$

$a_k(x)$ = the pixel position's feature channel k activation where $x \in \Omega$ with $\Omega \subset Z2$.

K = no. of classes and $p_k(x)$ is the estimated maximum-function.

The value of $p_k(x) \approx 1$ (Nearly equals to 1) for the k with the highest activation level a_k(x)

And The value of $p_k(x) \approx 0$ (Nearly zero) for all other k

$$E = \sum_{x\in\Omega} w(x)\log(p_{l(x)}(x))$$

where $l: \Omega \to \{1, \ldots, K\}$ is each pixel's actual label, and we established a weight map called $w : \Omega \to R$ to give some pixels more weight during training.

Precision: As measured by the ratio of true positive to the total of both true positive and false positive, precision is known.

$$\text{Precision} = \frac{TP}{(TP+FP)}$$

Recall: Recall is calculated by dividing the sum of true positives by the sum of false negatives.

$$\text{Recall} = \frac{TP}{(TP+FN)}$$

F1-Score: The harmonic mean of recall and precision is the term used to describe it. By multiplying the product by the sum of recall and precision, it is calculated.

$$\text{F1 Score} = \frac{2*precison*recall}{(precison+recall)}$$

Accuracy: The alteration of true positives and true negatives to all positive and negative data is the model correctness, a performance metric for machine learning classification models. In other words, correctness is the proportion of our machine learning model's predictions that correctly predicts a specific outcome.

$$\text{Accuracy Score} = \frac{(\boldsymbol{TP+TN})}{(\boldsymbol{TP+FN+TN+FP})}$$

where FP = False Positive,FN = False Negative, TP = True Positive and TN = True Negative.

Loss Function:

Loss functions calculate the difference between an estimated value and its actual value. A loss function links choices to the expenses they entail. Loss functions vary according to the work at hand and the objective that has to be achieved; they are not constants.

$$\text{Dice Loss} = DL(y,\hat{p}) = 1 - \frac{2y\hat{p}+1}{y+\hat{p}+1}$$

Balance Cross Entropy Loss $= L_{BCE}(y,\hat{y}) = -(\beta * y\log(\hat{y}) + (1-\beta) * (1-y)\log(1-\hat{y}))$

Here β is defined as $1 - \frac{y}{H*W}$

Dices coefficient can alternatively be thought of as a generalisation of Tversky index. With the use of coefficient β, it gives FP (false positives) and FN (false negatives) additional weight.

$$\text{Tversky Index} = TI(p,\hat{p}) = \frac{p\hat{p}}{p\hat{p}+\beta(1-p)\hat{p}+(1-\beta)p(1-\hat{p})}$$

When $\beta = \frac{1}{2}$,Another way to think about the Tversky index is as a generalisation of the Dices coefficient. With the use of coefficient β, it gives FPs and FNs (false negatives) more weight.

$$TL(p,\hat{p}) = =1 - \frac{1+p\hat{p}}{1+p\hat{p}+\beta(1-p)\hat{p}+(1-\beta)p(1-\hat{p})}$$

7. Results

To evaluate the efficacy of a classification model, a N x N matrix known as a confusion matrix is utilised, where N stands for the overall number of target classes. The actual objective values are compared to those predicted by the machine learning model in the matrix. It is a tabular overview of how many predictions a classifier made correctly and incorrectly. It is employed to evaluate a classification model's effectiveness. To assess a classification model's effectiveness, it is utilised to calculate performance indicators such as F1-score, recall, accuracy, and precision.

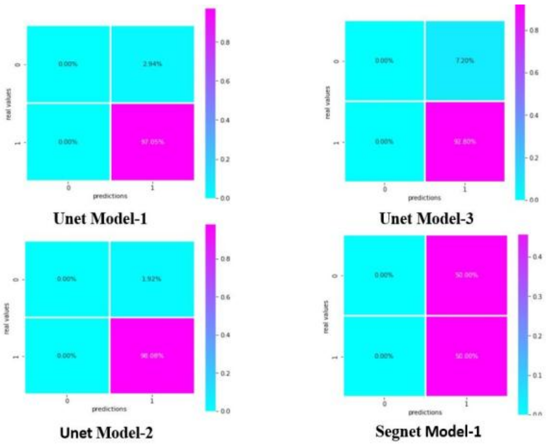


Figure 7: Confusion Matrix

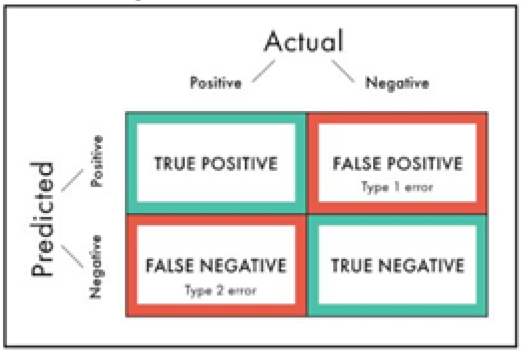


Figure 8: Binary Classification Problem (2x2 matrix)

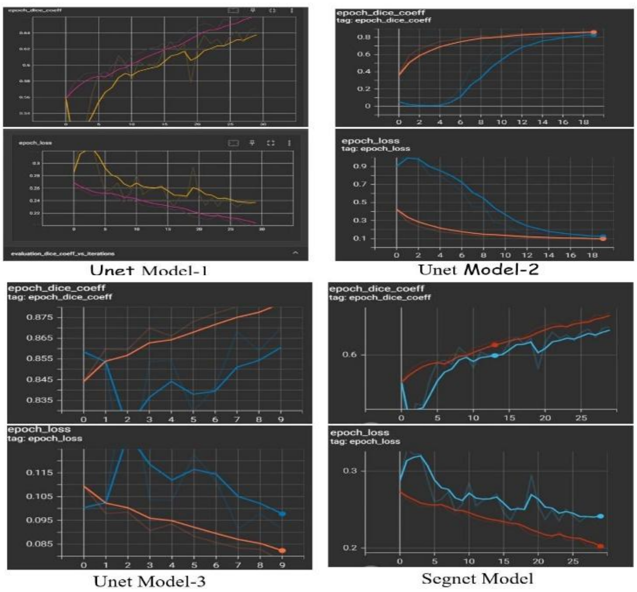


Figure 9: Accuracy & Loss Plot

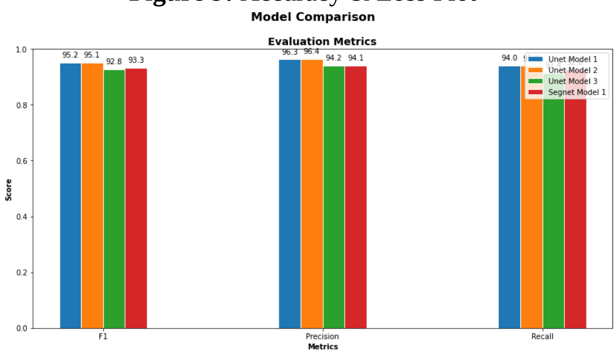


Figure 10: Model testing & comparison

The figure describes the comparison of models of different iterations of Unet model and SegNet model from the metrics i.e. F1 score, precision and recall.

Table 1: Comparison of Different Models

Model	F1	Precision	Recall	Accuracy
Unet1	95.16	96.32	94.03	91.05
Unet2	95.11	96.35	93.90	90.98
Unet3	92.76	94.15	91.40	86.83
SegNet	93.35	94.10	92.62	83.37

Here is the comparison of different segmentation evaluation index i.e. F1 score, precision, recall and accuracy for different iterations of models is performed and the best-performing model was retained and used for predicting the infected area of lungs.

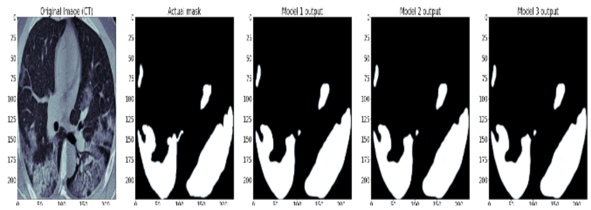


Figure 11: Output of Unet Model

- Unet Model 1 has 91.05% Accuracy
- Unet Model 2 has 90.98% Accuracy
- Unet Model 3 has 86.83% Accuracy

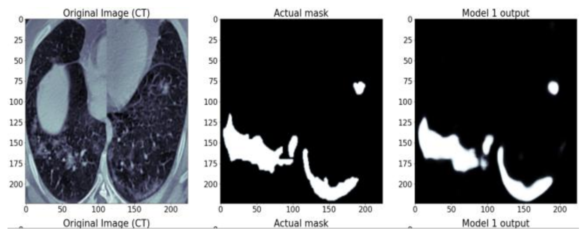


Figure 12: Output of SegNet Model

- SegNet Model has 83.37% Accuracy

Web & Mobile Application

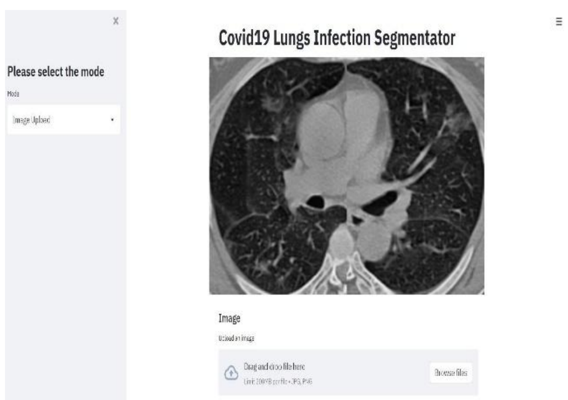


Figure 13: Web Application

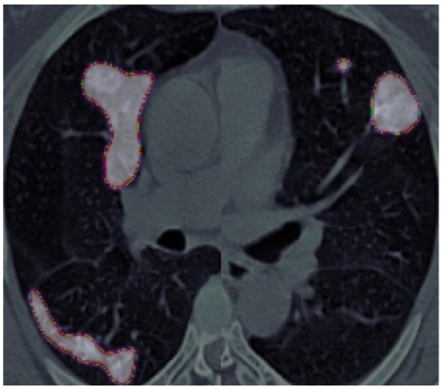


Figure 14: Infected Region

Figure 15: Mobile Application

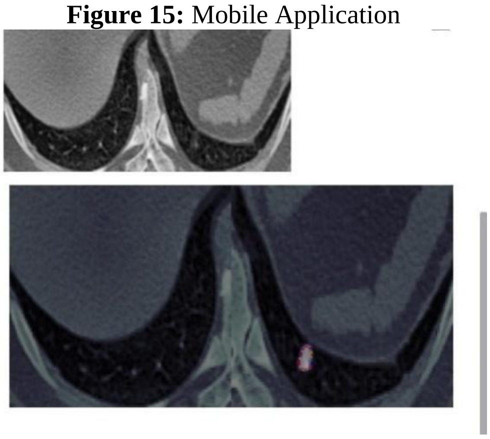


Figure 16: Infected Region

Here we found the infected region of lungs in both web application and mobile application. The purpose of this application is to found out the infected parts of the lungs easily and then proper required healthcare will be taken.

Dataset Used:
We used the dataset from zenodo.org [16] for this investigation. Twenty of his collection's COVID-19 CT scans that have been labelled make up the dataset. Two radiologists identify the right lung, left lung, and the infections. A third, more experienced radiologist then double-checks their findings. The dataset is about 1Gb in size.

8. Conclusion

On test data, our trained model scored a tremendous benchmark. The segmentation of lung infection mask is predicted with the highest level of accuracy (91.05%). Future model architectural improvements could raise this threshold, which would revolutionise the healthcare sector. The experiments show that the COVID-19 testing of our models is successful. In the future, we'll pay close attention to how serious COVID-19 is judged to be and work to extract more useful data from CT scans to fight the epidemic. The experiments show that the COVID-19 testing of our models is successful. In order to combat the outbreak, we'll continue to closely monitor COVID-19's severity and work to extract more useful information from CT scans. In order to identify pertinent elements in the CT scans and assist clinical practitioners in patient selection, additional explanatory investigations will be conducted on the models. This study will provide light on the COVID-19 detecting process. The study is still in the theoretical research stage, and the models have not yet been tested in actual clinical operations, despite the system's successful performance on publicly available datasets. Our technology is still in clinical testing situations and talk to medical experts to find out how they use it and what they think of the models. Consequently, in our future work, further enhance the models will be done.

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