

Lung CT Image Segmentation using Machine Learning

A Project Report Submitted in Partial Fulfillment of the Requirements for Award
of
the Degree of Bachelor of Technology in Information and Communication
Technology

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Submitted to
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Gandhinagar, INDIA, 382007

Declaration

I hereby declare that the project work entitled "**Lung CT Image Segmentation using Machine Learning**" is an authentic record of my own work carried out in Pandit Deendayal Energy University as requirement of B. Tech dissertation for the award of research institute as a requirement of B. Tech dissertation for the award of **Bachelor of Technology in Information and Communication Technology**. I have duly acknowledged all the sources from which the ideas and extracts have been taken. The project is free from any plagiarism and has not been submitted elsewhere for any degree, diploma and certificate.

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**Certificate of approval by HoD
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Certificate

This is to certify that the project entitled "**Lung CT Image Segmentation using Machine Learning**" submitted by **Khushali Patel(19BIT062)**, **Khushi Naik (19BIT064)**, **Hetarthi Mori (19BIT044)**, to the Department of Information and Communication Technology under School of Technology, PDPU in partial fulfillment of the requirements for award of the degree of **Bachelor of Technology in Information and Communication Technology** embodies work carried out under the guidance and supervision of Dr. Paawan Sharma, Associate Professor, ICT.

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This is to certify that the project entitled "**Lung CT Image Segmentation using Machine Learning**" submitted to the Department of Information and Communication Technology under School of Technology, Pandit Deendayal Energy University in partial fulfillment of the requirements for award of the degree of **Bachelor of Technology in Information and Communication Technology** is a record of work carried out by **Khushali Patel** (19BIT062), **Khushi Naik** (19BIT064), **Hetarthi Mori** (19BIT044), under my supervision and guidance in the Pandit Deendayal Energy University, Raysan, Gujarat, 382007.



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Certificate of approval by evaluators

The forgoing project entitled “**Lung CT Image Segmentation using Machine Learning**” submitted by **Khushali Patel** (19BIT062), **Khushi Naik** (19BIT064), **Hetarthi Mori** (19BIT044), to the Information and Communication Technology under School of Technology, PDPU is hereby approved as project work carried out and presented in a manner satisfactory to warrant its acceptance as a prerequisite of **Bachelor of Technology in Information and Communication Technology** degree for which it has been submitted. It has been understood that by this approval of the undersigned do not necessarily endorse or approve every statement made, opinion expressed or conclusion drawn therein but approve only for the purpose for which it is being submitted.

.....
Signature of Panel Members

Acknowledgement

The success and final outcome of this project required a lot of guidance and assistance from many people. It is my privilege to pledge the following few lines of dedication to those who helped me directly or indirectly in completing my project.

Firstly, I would like to express my special thanks to my mentor Dr. Paawan Sharma for his time and the efforts he provided throughout the semester. His suggestion and advice were truly helpful for the successful completion of the project. In this aspect, I am eternally grateful to him.

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Abstract

Lung tumor diagnosis at an early stage can increase the chances of survival of a patient. There are several methods used for the same in the medical field. However, here we have focused on lung CT image segmentation using U-Net and SegNet models. The dataset used here consists of CT scan images of 1080 patients containing lung nodules. The preprocessing is done to reduce the amount of noise and heterogeneity in the images. There were several steps involved: cropping of the parts not required for the segmentation, Transforming the image into HU (Hounsfield unit), and plotting various histograms to see the distribution of pixels. In this project, we have implemented the SegNet and U-Net models using PyTorch. Along with PyTorch, for Segnet we have used wandb (Weights and Biases.ai). As a result in the end we could observe the potential tumor regions in the images.

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Chapter 1

Introduction

Machine Learning has many use cases in the field of medicine and healthcare that have brought about revolutionary changes. These applications range from predicting stages of diseases, early prediction and diagnosis and in the discovery of new medication. In this context, our project aims to perform Image Segmentation on Lung CT Images to obtain tumour regions. Computed-Tomography (CT) is the best imaging technique in the medical field since it uses X-Rays to provide detailed information about the organ, with high resolution. A lung tumor is an abnormal growth of cells occurring in the lung tissue or in the airways that lead to the lung. Tumors can be categorised as malignant or benign. Malignant tumors indicate the onset of cancer, whereas benign tumors are harmless and are usually formed due to infections, scarring or inflammation. Finding out the type of lung tumor at an early stage is crucial, since the treatment plan can be made accordingly. Surgery decisions and personalized treatment plans can be made quickly and more accurately by finding out the region and size of the tumor.

The tumor appears as a shadow or spot in the lung region. Traditional methods in delimiting tumor boundaries involve manually annotating the tumour region or selecting the nodule by enhancement filters. However, these techniques are time consuming and costly for both the patient and the doctor. Furthermore, doctors and radiologists may need a second opinion for confirmation. Machine learning, especially deep learning models have the ability to process large amounts of information to achieve high levels of abstraction, and thus are suitable for the task of detecting tumors.

We investigate two Deep Neural Networks, SegNet and U-Net, for obtaining the tumours. Both are popular Convolutional Neural Networks aimed at performing semantic segmentation tasks. We will be comparing results obtained from both. Therefore by using CNNs, we can reduce the challenges of radiologists and quicken

the process of detecting early tumours.

1.1 Problem statement

In this project we aim to segment the tumour regions from the lung CT images which could help in calculating different size parameters. Our objective is to perform segmentation using Machine Learning Algorithms.

1.2 Objective

To increase the chances of survival from any tumour, it is important to detect the tumour at an early stage. This task has many complexities thus making it difficult for the doctors and skilled medical personnel to precisely diagnose the tumour and its severity. Image Segmentation is used to overcome this difficulty.

Although segmented images help doctors to perform diagnoses and reduce time, manual analysis is still required to treat the tumour. Information about the area and volume of the tumour can help determine the treatment plan and precise amount of dosage of medication. For this reason, we aim to obtain the volume of lung tumours by segmenting them.

1.3 Literature review

1) Messaya [1] in their research performed image segmentation of pulmonary nodules used Regression Neural networks. They focussed on finding nodule density and nodule volume doubling time. They used RNNs to derive a fully automatic segmentation system which uses a single cue point, a semi-automatic system which uses 8 cue points and a hybrid model that uses both FA and SA. It was found that although SA and hybrid segmentation systems were user-heavy, they were faster than the FA system.

2) Kumar [2] approached the tumour segmentation process by using various evolutionary algorithms - K means clustering, K-median clustering, Particle Swarm

Optimisation, Inertia weighted PSO and guaranteed convergence PSO. It was found that GCPSO worked best due to its near-perfect results when compared with manually segmented nodule images.

- 3) Tumour volume calculation has been carried out by Mahmood [3]. They segmented and extracted lung tumours using K-means clustering, followed by a semi-automatic seeded region growing algorithm. Tumour area was calculated for the region and by stacking the slices, they were able to find the volume and simulate a 3D visualization of the tumour.
- 4) Yosandha [4] also performed tumour volume calculation, but for the Treatment Planning System. They segmented the tumour into different regions, namely - clinical target volume, gross tumour volume, planning target volume and organs at risk. Since the volume was calculated for different methods, they used an active contour segmentation method.
- 5) Saood [5] and Skourt [6] have both applied U-Net neural networks to obtain the lung parenchyma. Saood [5] have used U-Net and SegNet both for differentiating diseased lung tissues from healthy ones for Covid-19 detection.
- 6) Nishino [7] in its research performed the segmentation of tumour and presented the result in a three-dimensional form. They aimed at providing the volume and Hounsfield unit of the tumour as an output. HU is a CT attenuation coefficient of the segmented tumour. Using CT and multidetector-row technology, the volume of the infected area was calculated. The limitations which were discussed in the paper by the authors were the lack of thin-slice CT images and the considerably smaller dataset.
- 7) Carvalho [8] has worked on detecting the abnormal tissue area of the lung using DCNN and the segmentation is handled by the U-Net method. DCNNs are generally used for the detection of patterns in images. The proposed models turned out to be highly precise at the same time efficient as the hardware requirement is comparatively less in this case. Further, it has been mentioned that the accuracy can be improved by using 3D architecture.
- 8) Wasudeo [9] in their research emphasized the importance of early detection of lung cancer. They used image processing and machine learning techniques such as SVM to detect lung cancer regions in the CT images. The features which were extracted here include area, volume and eccentricity which provide information about the severity of cancer.

- 9) Focusing on the complexity which is involved in extracting lung tumours, Zhang [10] in their review paper mentioned the use of SVM for classification. It emphasized the use of CAD (Computer Aided Diagnosis System) which can be useful in the early detection of lung nodules.
- 10) Zhao [11] in his research used morphological methods for the segmentation of the lung. They implemented the method of classification using U-Net and CNN on the CT images. To boost the training of the model and increase its performance they used GAN.

1.4 Plan of execution

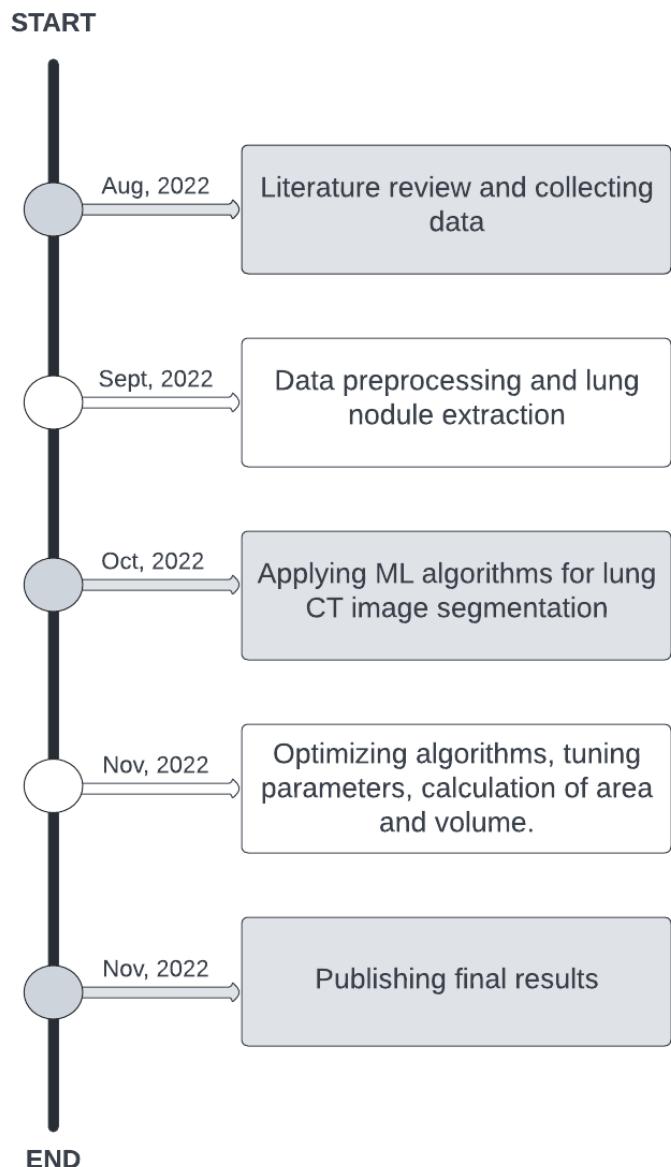


Figure 1.1: Timeline

Chapter 2

Experimental Methods and Results

In this chapter, we have discussed about the methods that were used to derive the output with detailed analysis. The results are also shown.

2.1 Methods

Medical image segmentation is a sensitive task, as it deals with the human lives. Therefore, utmost care needs to be taken of the data, therefore preprocessing is performed. It is imperative to remove noise, enhance images and bring them in the correct format before using them. This is known as preprocessing.

Image Segmentation is the process of partitioning the pre-processed CT scan images into the region we require, based on some homogeneity condition. Here, we want to delimit a region of interest (tumor) from the whole image, therefore, we do not use any prediction or categorical method. Instead, we train the model to identify pixel values that correspond to the tumor. This gives us a segmentation mask, an image, as the final output. The below diagram gives a brief overview of the steps we have followed.

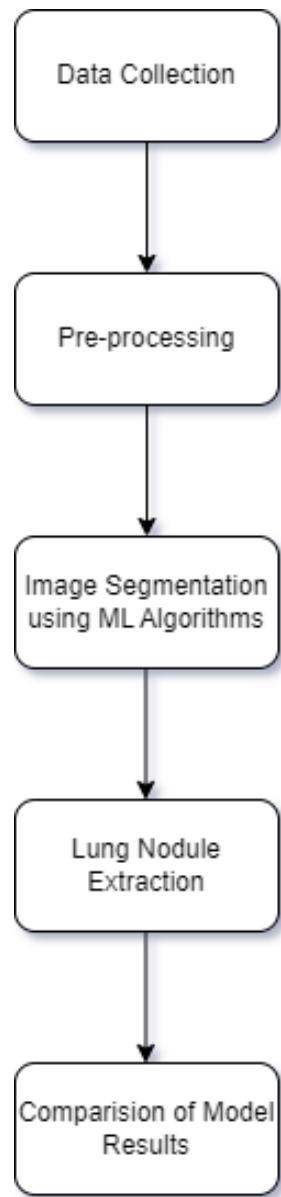


Figure 2.1: Flowchart

In this project, following steps are used:

1. The first step to realize the solution is to gather the lung tumour database and scrutinize the collected images. The data in this project is collected from the Medical Segmentation Decathlon (2018).

2. It is necessary to enhance the images and make them interpretable in order to detect the lung nodules accurately. It includes resizing the image, taking uniform slice thickness, HU transform, and normalization of pixel values.
3. Next step is to segment the images with the help of Machine Learning Algorithms. In this project we will make a baseline model using SegNet and U-Net Neural Networks.
4. Features are extracted with the help of above mentioned algorithms, and loss functions are calculated. We obtain our region of interest, which is the lung nodule area.
5. The CT scan provides 2D images of the lung nodules that gives area of the tumour. These 2D images can be stacked together to determine the volume.

Detailed process of implementing all these steps are given in the subsequent sections.

2.2 Detailed Analysis

2.2.1 The Dataset

The TCIA database - LIDC-IDRI consists of thoracic CT scans containing lung nodules. Along with the CT images, it also includes marked-up annotated lesions. The dataset contains Ct images from a total of 1018 patients, covering seven academic centres and eight medical imaging labs.

For each subject, around a couple hundred image slices are present. An associated XML file is also given for each subject, in which the results of a two-phase image annotation process has been recorded. The annotation process has been done by four experienced thoracic radiologists manually. Initially, each radiologist independently reviewed each CT scan and marked lesions. In the subsequent phase, each radiologist independently reviewed their own marks along with the anonymized marks of the three other radiologists to reach a final opinion. The goal of this process was to identify as completely as possible all lung nodules in each CT scan without requiring forced consensus.

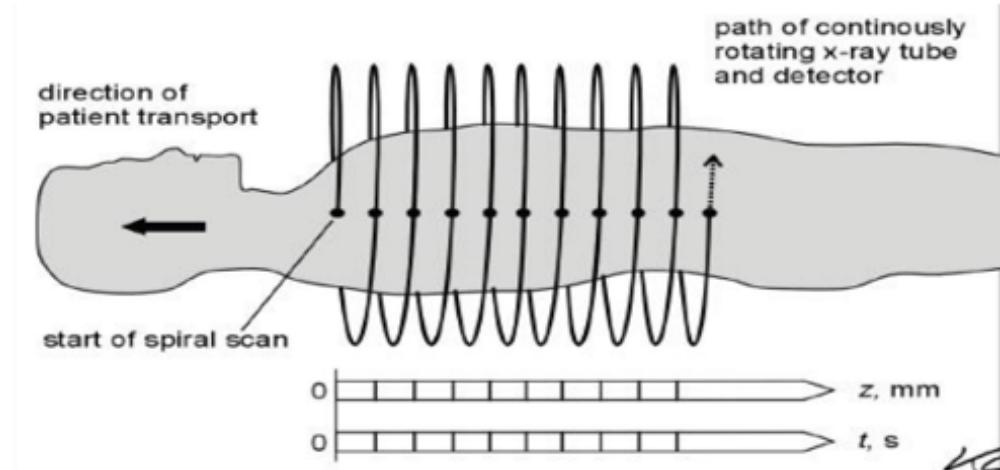


Figure 2.2: Process of CT imaging

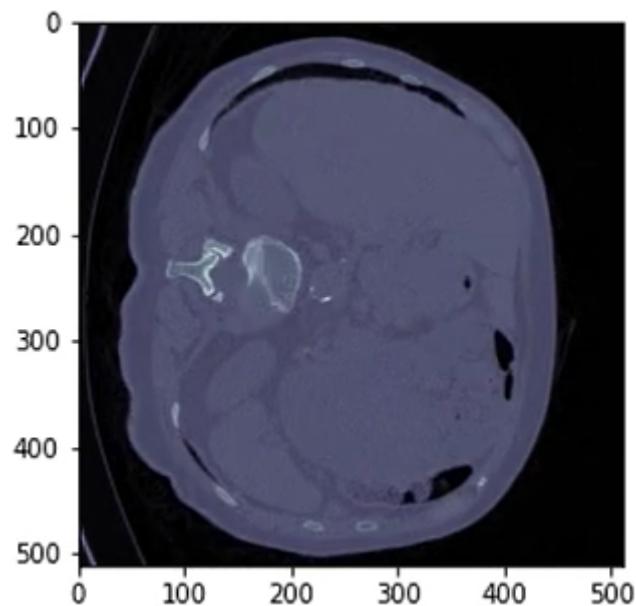


Figure 2.3: Slice No. 60

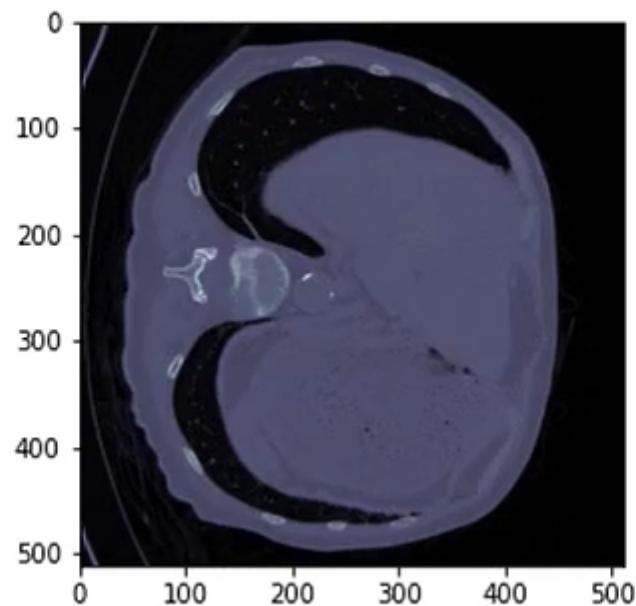


Figure 2.4: Slice No. 100

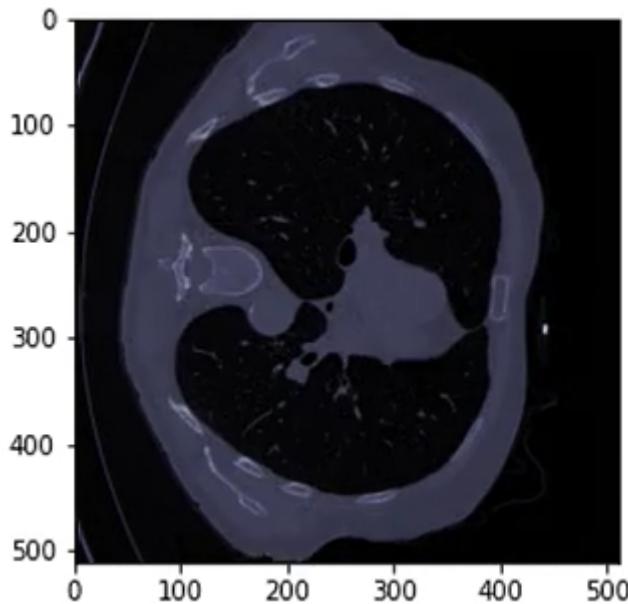


Figure 2.5: Slice No. 200

For this project, we took a subset of this dataset by taking data from the Medical Segmentation Decathlon (2018). The MSD dataset is derived from the LIDC-IDRI dataset, but instead of using XML annotations and DICOM files, the MSD provides data in the form of Nifti files along with segmented tumor masks. This makes it computationally less expensive, and in total the dataset has been reduced to just over 10 GB in size. It covers 63 subjects in the training set and 32 subjects in the test set.

2.2.2 Pre-processing

Working with raw image files is challenging, given the amount of noise and heterogeneity. Therefore, before the data is ready for consumption by the model, it needs to be pre-processed. The following steps were performed to accomplish this:

- Perform cropping of parts that we do not require for the segmentation task. This reduces complexity and helps the network learn. As an example, we might skip the first 30 slices (from lower abdomen to the neck).
- Transforming to HU: We transform the image into the Hounsfield Unit (HU) scale. Hounsfield Unit is a relative quantitative measurement of the intensity

of radio waves. While taking CT images, denser regions of the area under consideration absorb more quantities of X-rays, making them appear brighter in the CT scan. Whereas areas with less density absorb a lesser quantity of X-rays, making them appear darker in the CT scan. The CT scanner yields roughly 4000 gray tones that cannot be differentiated by our eyes. That is why the HU scale is used to normalize various gray tones with respect to the densities of objects in the CT scan.

- HU transform normalizes the values of water and air. Water has HU 0 and air has HU -1000. Using this property, the images of different parts of lungs can become comparable with respect to their densities. Therefore, we can examine which region of the lung contains tissues, blood vessels, pulmonary nodules etc. and which regions are hollow, by transforming DICOM image into HU image. We have performed this by using the concept of Rescale intercept and Rescale slope to linearly transform original pixel values to HU normalized pixel values. The image obtained after doing so, is as follows:

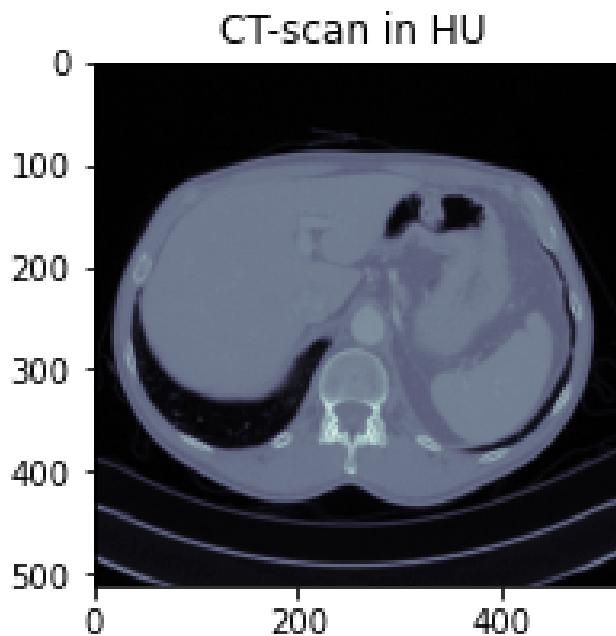


Figure 2.6: CT-Scan in HU

- Pixel array distribution: Next, we plot various histograms to see the distribution of pixels and their properties. From this we obtain information about gray levels, pixel spacing and thickness of slice.

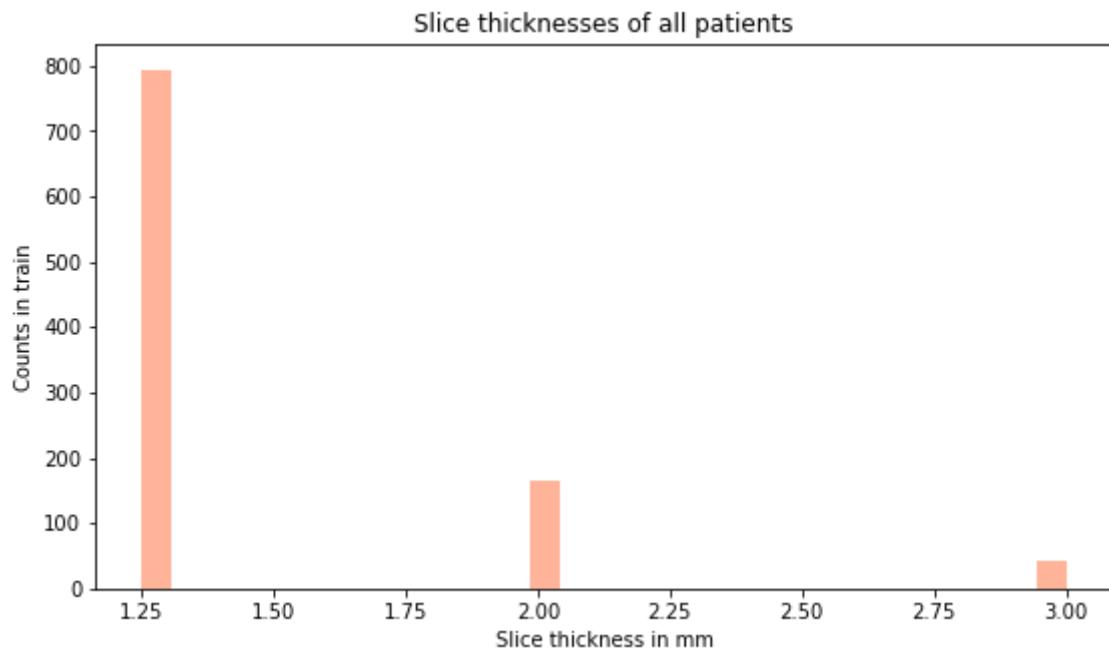


Figure 2.7: Slice Thickness Plot

- This task will be done on a slice level, hence we use 2D images and pixel data, rather than subject level (3D) with pixels. Therefore, we store the pre-processed data as 2D files, because reading a single slice is much faster than loading the complete NIfTI file.
- In conjunction with HU transform, we also normalize the CT images values. The grey level values range from -1000 to 3071. Thus we can normalize by dividing by 3071.

The pre-processed data then gets stored in another folder as numpy files, to be fed into the Neural network to perform segmentation. Next, we split the training data into train and validate sets. We do not take a fixed ratio, instead, we use the measure of `train_size` which is calculated as:

```
train_size = number of valid_files * (1-val_split)
where, val_split = 0.1
```

In the dataset, the files end with the subject number. Thus, files ending with subject numbers lesser than `train_size` will be assigned to the train dataset. Files

ending with subject numbers greater than `train_size` will be added to the validation dataset.

2.2.3 Models

U-Net

U-Net is a special type of architecture designed for a fully convolutional neural network that specializes in image/semantic segmentation. Semantic segmentation is a procedure where a mask is created that shows where on the image a specific object is located and also provides its dimensions. U-Net is fully convolutional since it contains only convolution layers and does not contain any dense or fully connected layers. Because it is U-shaped, it is called U-net.

The architecture consists of 2 paths, a left path and a right path. The path on the left side is called the contraction path or the encoder path, whereas the path on the right side is called the expansion path or the decoder path.

The encoder uses convolutions and max-pooling operations. The architecture is build of many levels, every level consists of two 3x3 convolutional layers each followed by a Re-LU (Rectified Linear Unit) activation unit. The transition between those levels is handled by a 2x2 max-pooling unit with stride value as two for the down-sampling also known as sub-sampling. Basically the size of the input is reduced at each level for the next level. The information at each level is condensed and at the receptive field the size of the input halves and the number of channel doubles with every level that we go to the bottom of the U-shape.

The decoder uses the same architecture at each level but with slight variations. For localization, skip connections are used where the feature maps of the encoder are concatenated to the output of the transposed convolutions of the same level. To get an output of the same size as the input, up-sampling is done. For that purpose, 2x2 transposed convolutions also known as deconvolutions are used. At each level in the up-sampling process, the size of the data increases but the channel halves.

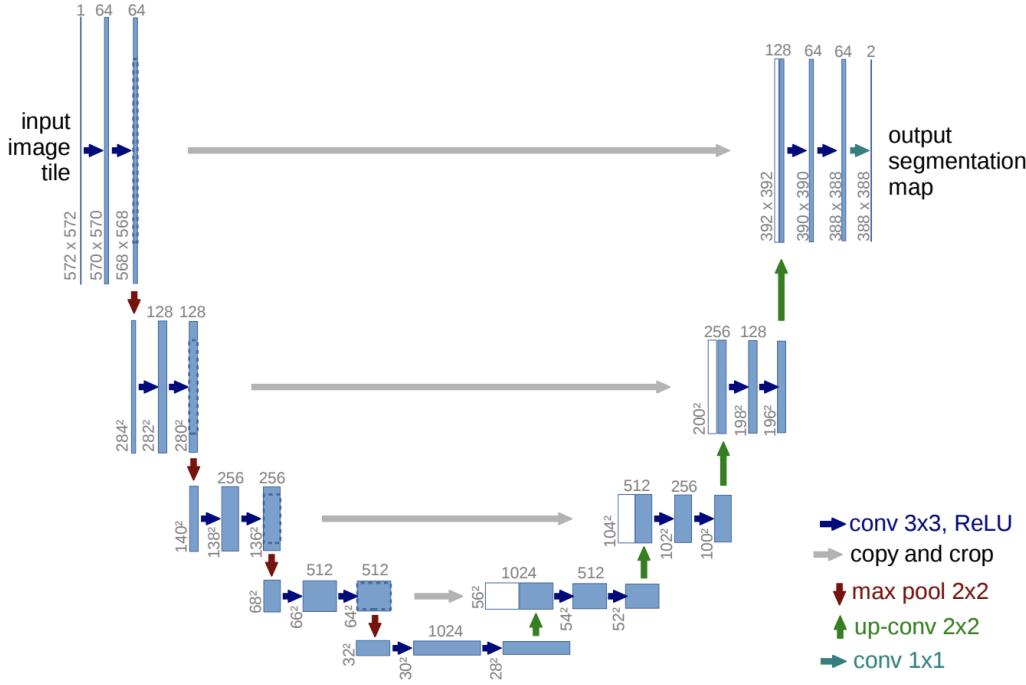


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

Figure 2.8: U-net

SegNet

SegNet is a deep convolutional encoder-decoder architecture for image segmentation and visual scene understanding. SegNet can produce the segmentation of colour images in real time. The input to the system is a single colour image and the system outputs a semantic label for each pixel. SegNet only requires RGB input. SegNet consists of 3 main modules: the encoder, the decoder and additionally a pixel-wise classification layer. The SegNet encoder's architecture is similar to the VGG16 network which consists of 13 convolutional layers. For the pixel-wise classification, the decoder maps feature maps that are of low resolution to the feature maps with full input resolution. In order to perform non-linear up-sampling, the decoder uses pooling indices that are computed in the max-pooling step.

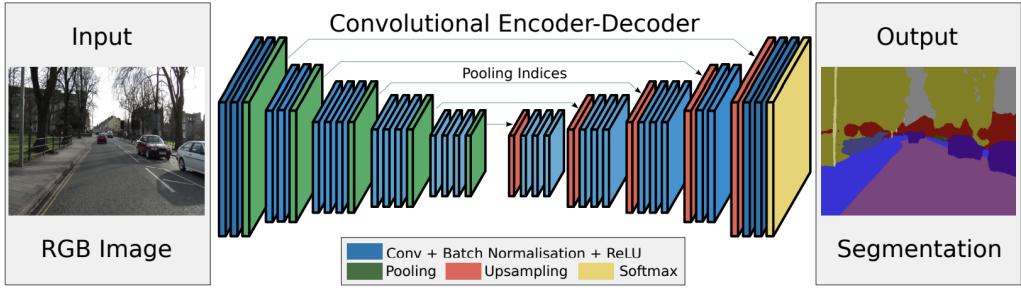


Fig. 2. An illustration of the SegNet architecture. There are no fully connected layers and hence it is only convolutional. A decoder upsamples its input using the transferred pool indices from its encoder to produce a sparse feature map(s). It then performs convolution with a trainable filter bank to densify the feature map. The final decoder output feature maps are fed to a soft-max classifier for pixel-wise classification.

Figure 2.9: SegNet

The main difference between U-Net and SegNet is that in SegNet while the expansion path or the decoder is given the input from the compression path or the encoder, only the pooling indices are transferred, thus using less memory. On the other hand in U-Net, the inputs given to the expansion path or the decoder from the compression path or the encoder are entire feature maps, thus using more memory.

2.2.4 Fitting the Data

The MSD dataset has already divided the dataset into two folders - ImagesTr which comprises 63 gzip files of training data for each subject, and ImagesTs, which comprises 32 gzip files of testing data.

For training the data, we use the pre-processed train dataset we have obtained. This project has implemented both the SegNet and U-Net models using PyTorch. We have trained the models on an equal amount of data - 14484 training and 1283 validation images.

Along with PyTorch, for SegNet, we have used wandb (Weights and Biases.ai) which is an online dashboard for machine learning. Model logging and check-pointing has been done using wandb. For example, we can track model performance metrics, hyper-parameters, gradients, system metrics, and output files. For example, we can see the segmentation mask start to identify potential regions of tumor at a particular step:

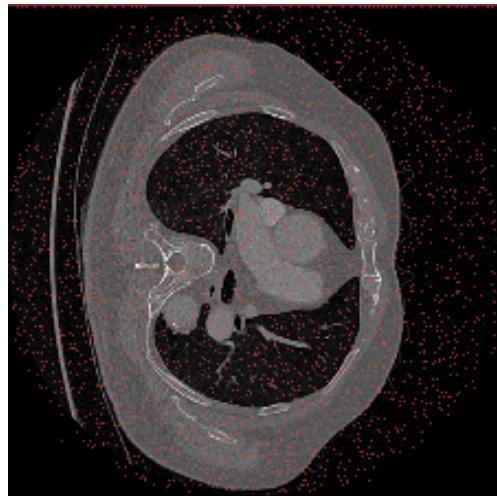


Figure 2.10: Appearance of Segmentation Mask

Model details are as shown in Table 2.1.

Model	Output Shape	Loss function
SegNet with MaxPool2d	224,224	CrossEntropyLoss()
U-Net	256,256	BCEWithLogitsLoss()

Table 2.1: Model Details

The data was trained in 20 epochs, taking batch size as 4 and using hosted GPU runtime for SegNet. The data for U-Net was trained in 30 epochs, taking batch size as 8 and using hosted GPU runtime. For U-Net, we have taken TensorBoard logger for checkpointing.

2.2.5 Loss Functions

Dice Score:

Dice score or coefficient is used to measure the similarity between two sets of data.

Dice Score =

$$\frac{2 * \text{Area of overlap}}{\text{Total no of pixels in both images}}$$

$$\text{Dice Score} = 2 * |X \cap Y| / (|X| + |Y|)$$

Here, X and Y are two sets in which the similarity is to be found

$|X \cap Y|$ = Intersection of sets X and Y

Binary Cross Entropy:

Binary cross entropy, also known as Log Loss and is used for binary classification. In binary cross entropy, each of the predicted probabilities are compared to the actual class output which can either be 0 or 1. Then it calculates the score based on how close or far the predicted values are from the actual value.

$$\text{Log loss} = \frac{1}{N} \sum_{i=1}^N - (y_i * \log(p_i) + (1-y_i) * \log(1-p_i))$$

Intersection over Union (IoU):

Intersection over Union quantifies the degree of overlap between two boxes. It is used to evaluate the overlap of the actual value or the ground truth and the predicted region. IoU ranges between 0 and 1 where 0 represents no overlap and 1 represents perfect overlap.

IoU is calculated as follows:

$$= \frac{\text{Area of Overlap}}{\text{Area of Union}}$$
$$= \frac{\text{Area of Intersection}}{(\text{Ground Truth} + \text{Predicted Box Area} - \text{Area of Intersection})}$$

2.3 Results

The discussed methods are practically implemented using PyTorch Lightning. The graphs were obtained by logging each epoch using wandb and TensorBoard libraries. The code and results were verified. The dice score and loss values obtained are as shown in the table below:

SegNet	
Dice Score	0.88247289
Training Loss	0.4741
Validation Loss	0.5159
U-Net	
Dice Score	0.8965917
Training Loss	0.00182
Validation Loss	0.651

Table 2.2: Performance of SegNet vs U-Net

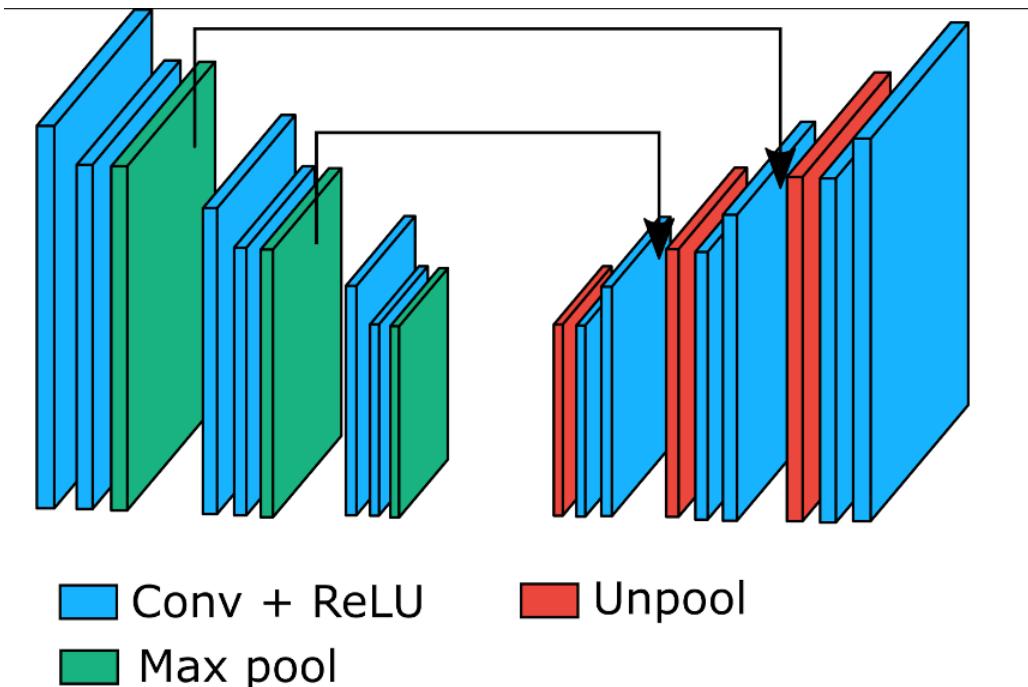


Figure 2.11: SegNet Model

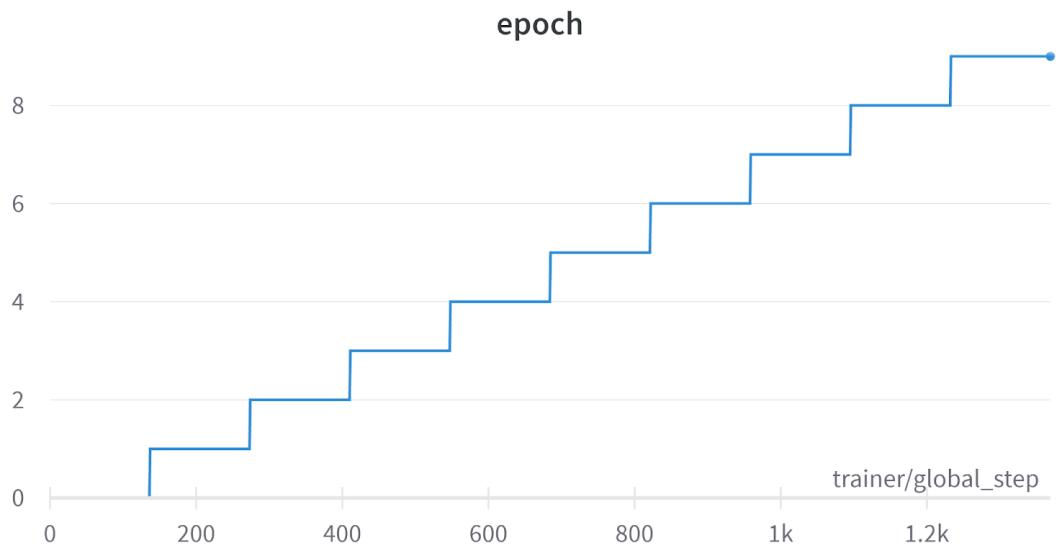


Figure 2.12: epoch 10 for SegNet

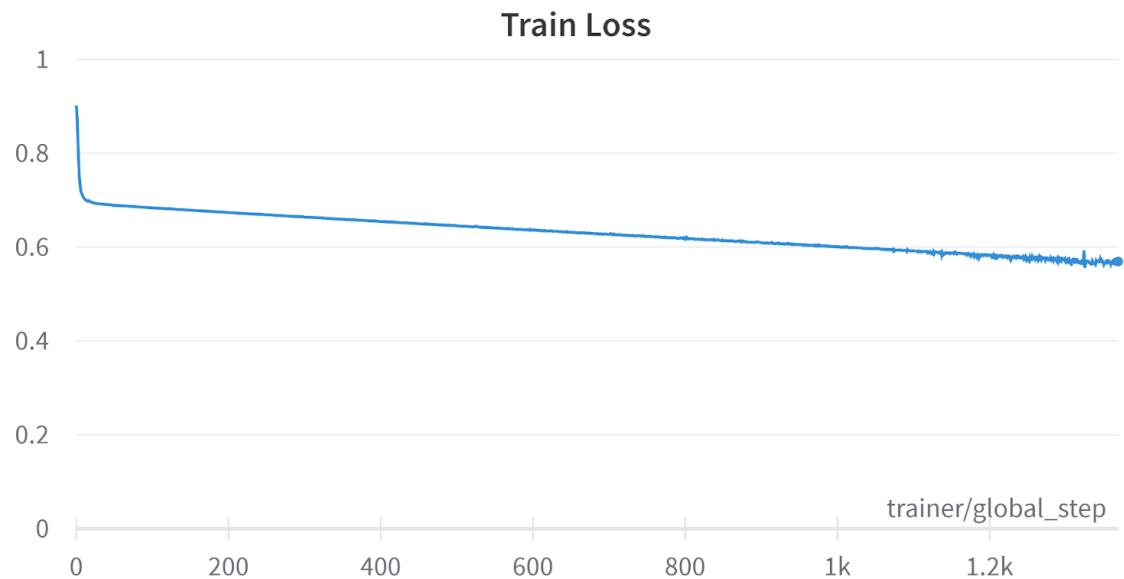


Figure 2.13: Training Loss of SegNet

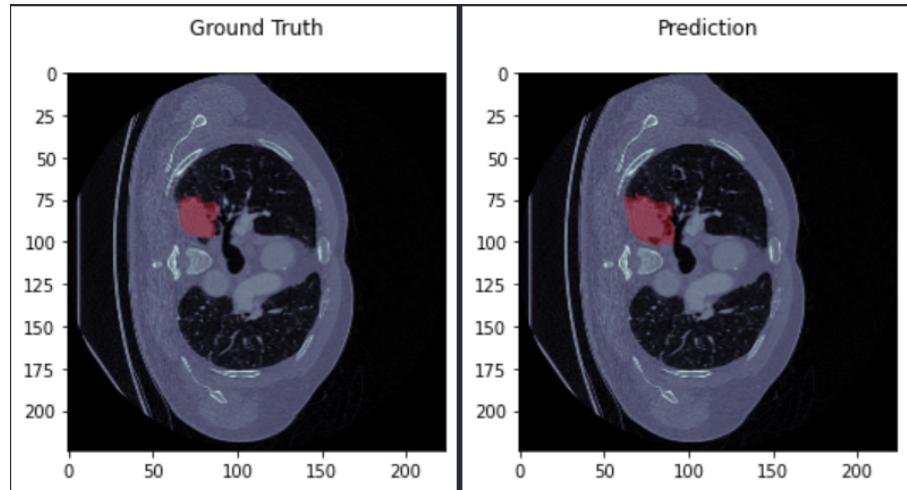


Figure 2.14: Predicted Tumor Vs Ground truth - SegNet

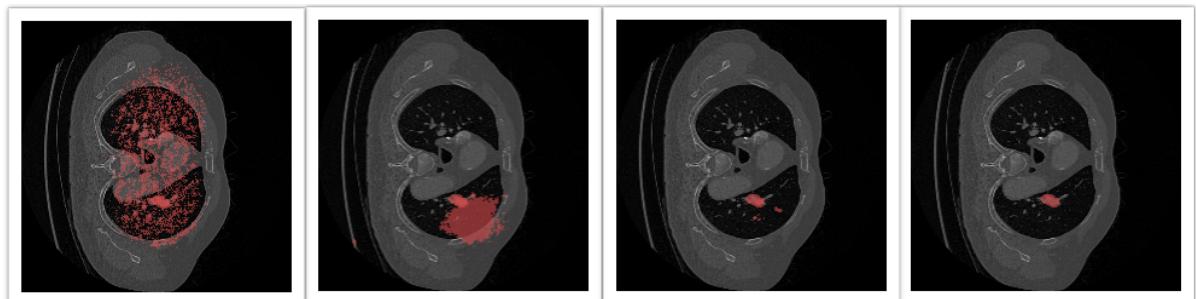


Figure 2.15: Segmentation Process of SegNet

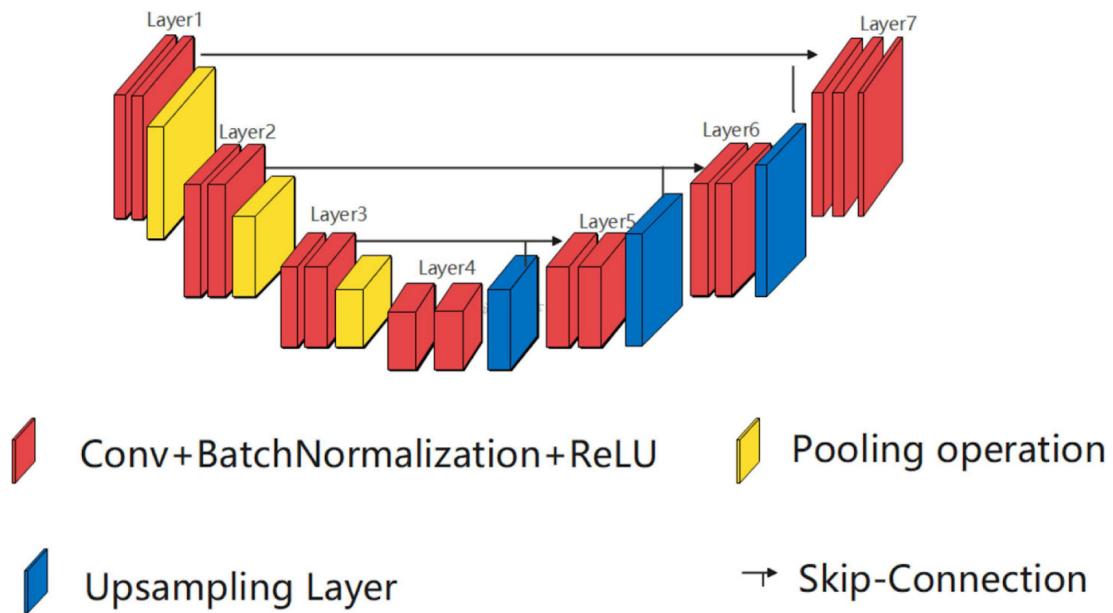


Figure 2.16: U-Net Model

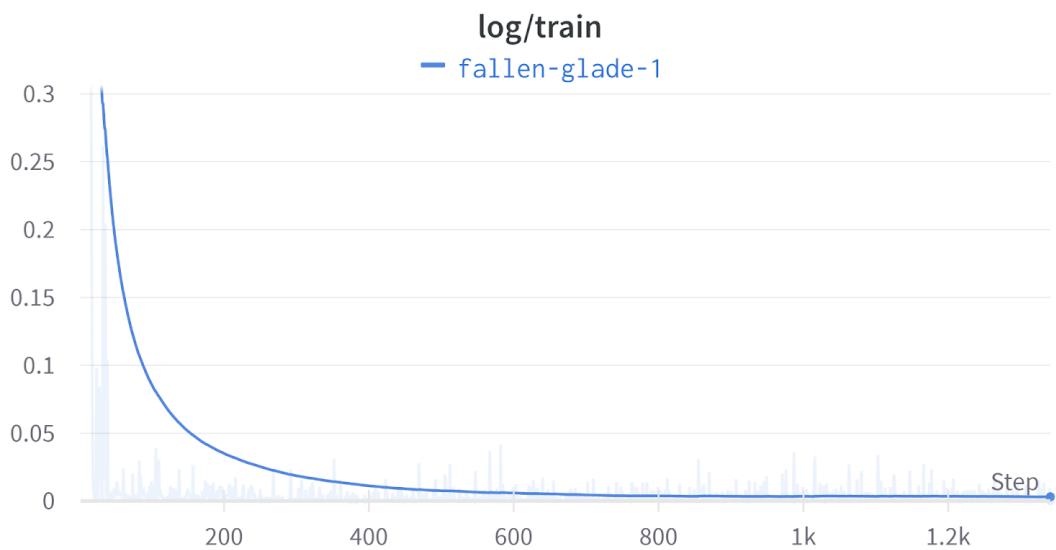


Figure 2.17: Training Loss for U-Net

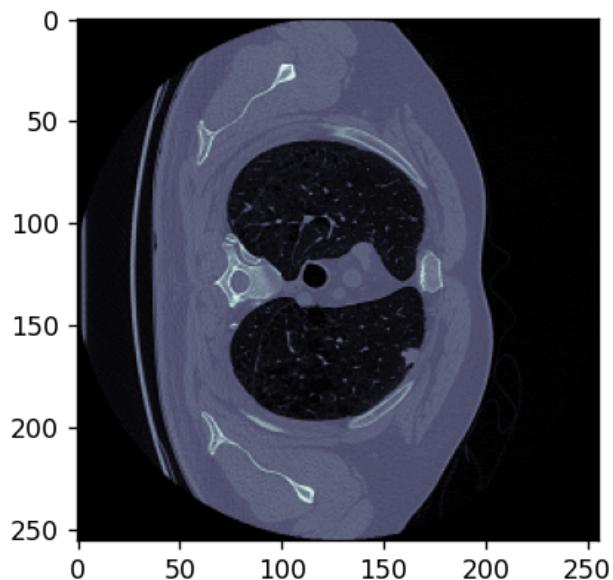


Figure 2.18: Actual Slice for U-Net

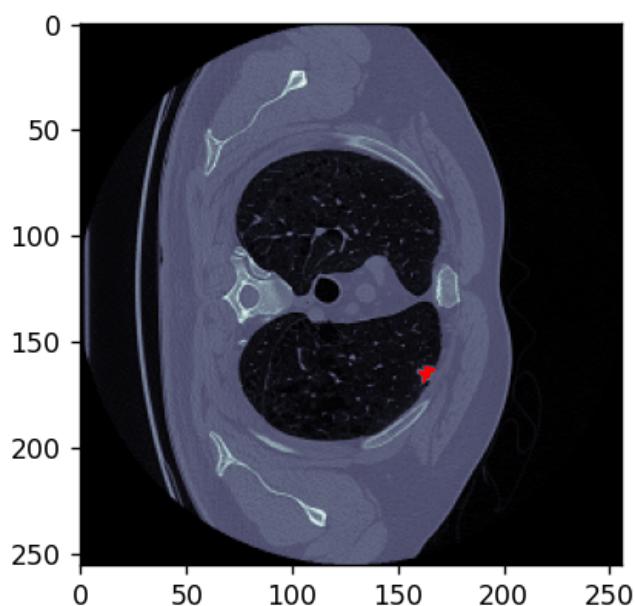


Figure 2.19: Ground Truth - U-Net

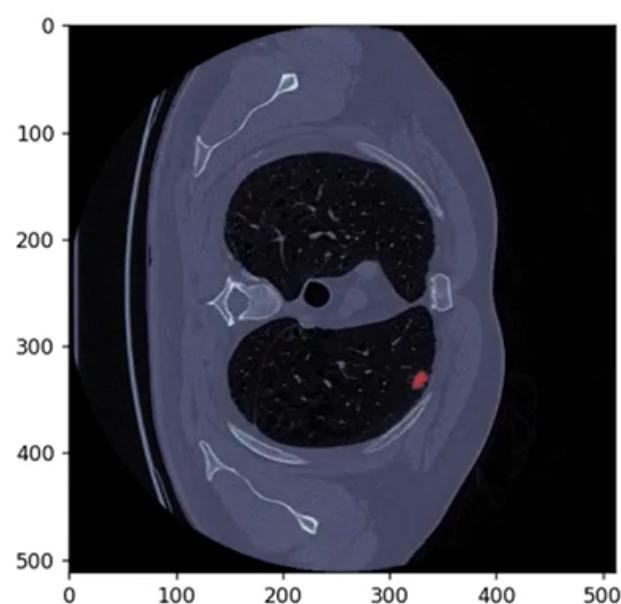


Figure 2.20: Predicted - U-Net

Chapter 3

Discussion and conclusion

3.1 Conclusion

In this project, we presented a comparison of two deep neural network models for lung nodule segmentation. Using the U-net architecture, we obtained an accurate segmentation with 0.8967 Dice-coefficient index and SegNet architecture gave a very similar score of 0.8825. The results show that both models perform accurately, with U-Net having a slight advantage over the SegNet, in producing a high quality segmentation mask. Our objective in the next stage is to calculate the area and volume of the segmented tumor region.

3.2 Limitations

- It is difficult to obtain ground truth for medical data, since there is always a need for medical professionals to verify, label, and manually annotate data.
- For medical data, there are varying imaging protocols and differences in annotation procedures. This introduces lots of heterogeneity while collecting the data.
- Lack of infrastructure - even with hosted runtime, we were not able to use the entire dataset for training. We were limited in reducing the epoch and using only a part of the dataset for training. Thus we had sparse data and less computing resources. For very large datasets, we need many GPU cores, or even TPU. This would improve the final accuracy.

- Domain adaptation problem - image segmentation algorithms cannot be generalized for use for segmenting other biomedical entities. For example, this model made for lung segmentation will not work for brain segmentation, because the architecture will differ.
- Oversampling- Lung tumors are often very small, thus we need to make sure that our model does not learn a trivial solution that simply outputs 0 for all pixels.

3.3 Future work

Our main objective will be to calculate the area and volume of the segmented nodules. The proposed method is to calculate the area using:

$$A = \sum_{r, c} I(r, c)$$

The volume can be found using the Frustum model:

$$\text{Volume} = \sum \left(\frac{h}{3} (A_1 + A_2 + \frac{A_1 \times A_2}{2}) \right)$$

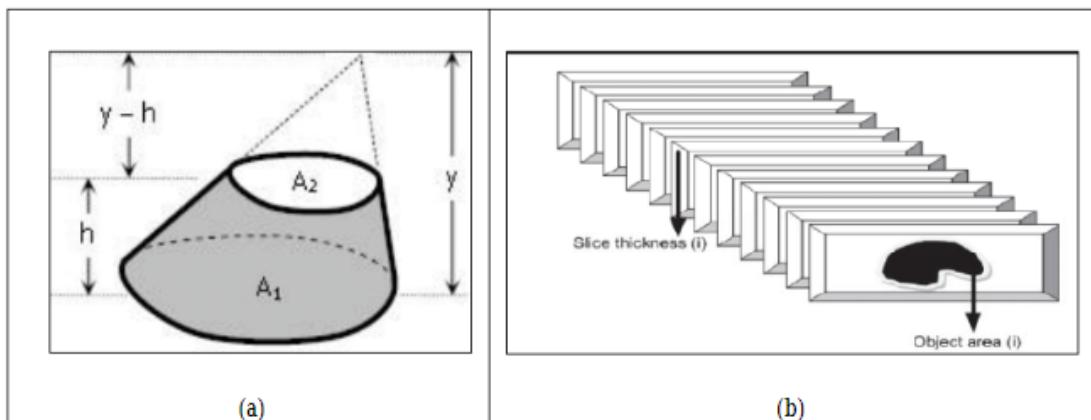


Figure 3.1: Frustum Model Volume Calculation

In order to verify the correct estimated size, we need to have some ground truth. This involves collecting data from other sources since this dataset does not contain size information. Therefore, this is to be done in the future.

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Abstract

Lung tumor diagnosis at an early stage can increase the chances of survival of a patient. There are several methods used for the same in the medical field. However, here we have focused on lung CT image segmentation using U-Net and SegNet models. The dataset used here consists of CT scan images of 1080 patients containing lung nodules. The preprocessing is done to reduce the amount of noise and heterogeneity in the images. There were several steps involved: cropping of the parts not required for the segmentation, Transforming the image into HU (Hounsfield unit), and plotting various histograms to see the distribution of pixels. In this project, we have implemented the SegNet and U-Net models using PyTorch. Along with PyTorch, for Segnet we have used wandb (Weights and Biases.ai). As a result in the end we could observe the potential tumor regions in the images.

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