Assignment 3

Introduction:

Our goal in this assignment is to classify brain tumor in human brain. Glioma (brain tumor) is divided into glioblastoma (HGG) and lower grade glioma (LGG) with HGG being an aggressive and life-threating tumor. Dataset consists of tumor image, segmentation map and label. Image consists of four channels and segmentation map contain subregions, each with a different pattern on brain MRI scan. Following figure helps in visual understanding of dataset.

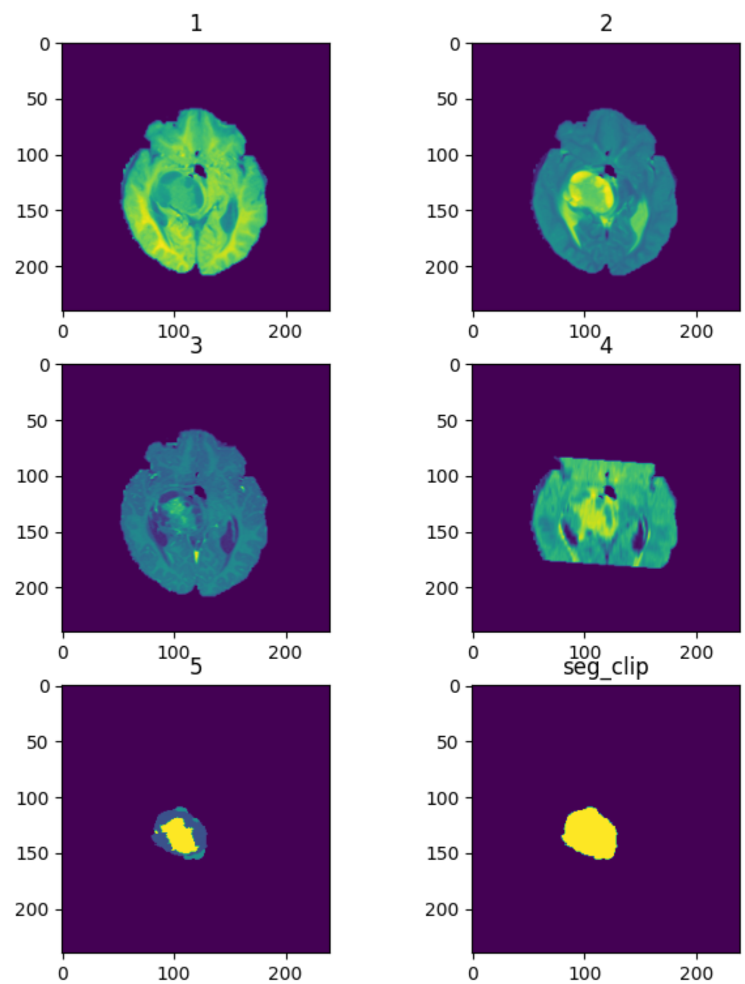


Figure 1: MRI image channels and label

Assignment is divided into three parts which are as follows

1. Performing Segmentation using **Region Growing** method using different starting point.
2. Performing segmentation using **Graph Cut** method.
3. Performing segmentation using **U-Net** deep learning model.

Part1:

In the first part we use **Region Growing** method for segmenting the brain tumor. Image contains different regions and these regions have similar value pixels within themselves. Region growing method perform segmentation based on similar pixel values within a region. This method takes seed value as a start location and starts comparing neighboring pixel values from that location. If neighboring pixels are similar, they become part of the segmented region. I used an opensource repository form GitHub for this task (https://github.com/zjgirl/RegionGrowing-1)

Before region growth we have to apply thresholding to enhance the regions of the image. It was found that region growing doesn't work well for all the channels of an image as they contain different information in them. After experimentation it was found that 2nd channel of the four-channel image produces best results for thresholding. Difference in thresholding can be visualized in the following figure.

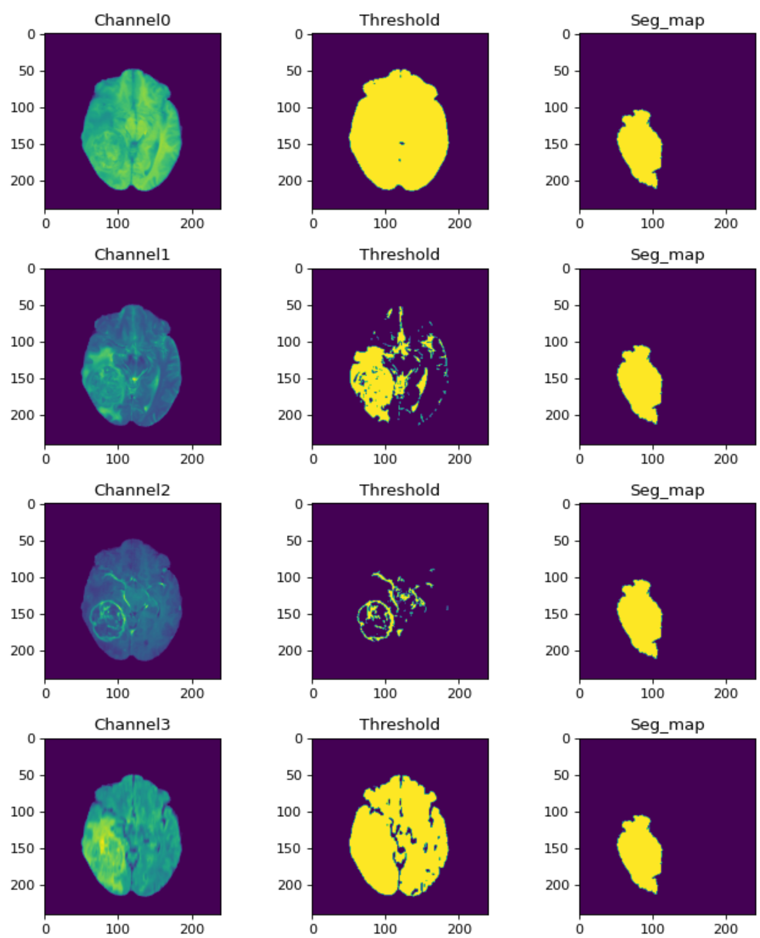


Figure 2:Thresholding result on different channels

For obtaining seeding point I used the median point of the label provided in the dataset. This seeding point along with image obtained from thresholding is used for region growth algorithm. Nine images from test dataset were selected and used for segmentation task.

Results:

This technique achieved a dice score of **0.65** and when tested on whole test dataset, this score drops to **0.54**. Some of the results are shown below.

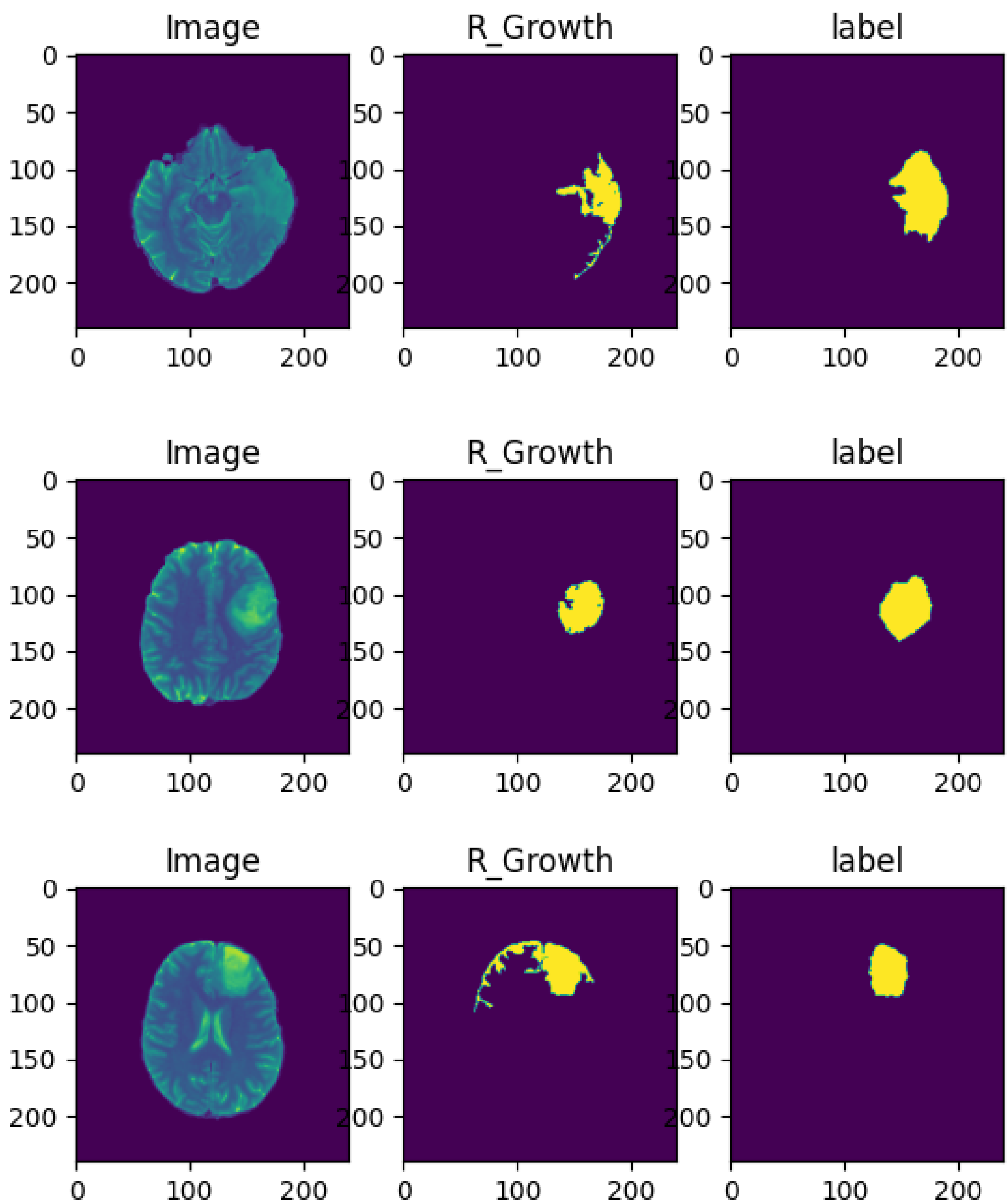


Figure 3: Results

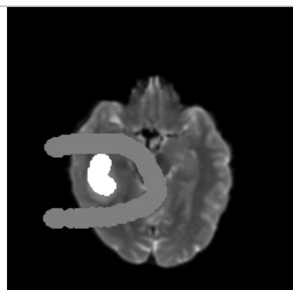
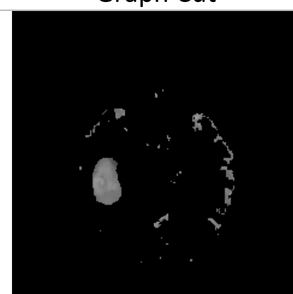
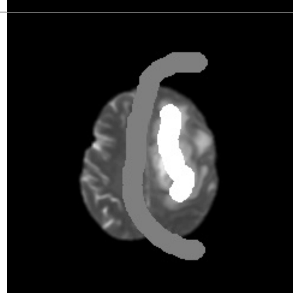
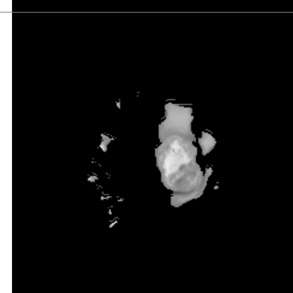
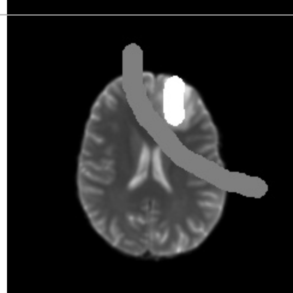
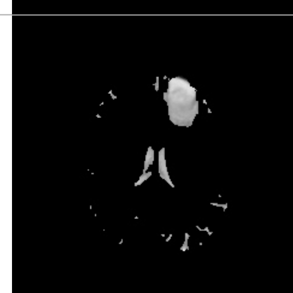
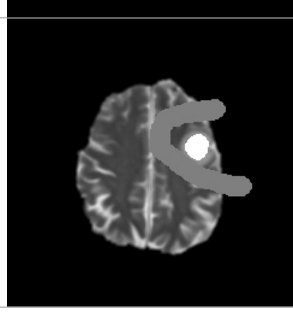
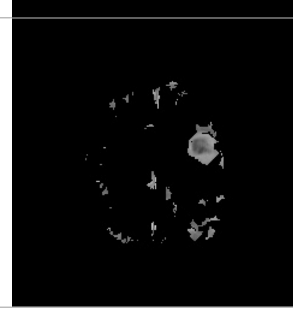
Part2:

In this part we use the same dataset as used in Part1 to perform segmentation using **Graph Cut** algorithm. Algorithm depends on user input for drawing a scribble for foreground and background of an image. Based on these scribbles, algorithm segments the image. I used this opensource repository for this task (https://github.com/ishank26/svm-GraphCut).

Results:

This technique achieved a dice score of **0.54**. Performance of this algorithm mainly depends on the quality of scribbles used for foreground and background. Foreground scribble is represented by white line and background scribble is shown by grey line. Some of the results are visualized in the following figures.

Table 1: Graph Cut results

Scribble	Graph Cut
	
	
	
	

Part 3:

In this part we have to train a U-Net segmentation model. Input of this model is the four channel MRI image and the network outputs a segmentation map. For experimentation I used this repository for U-Net segmentation model (https://github.com/milesial/Pytorch-UNet). U-Net was trained on whole training dataset and dice score was calculated using all of the test dataset.

A four step U-Net was used which include four down sampling and four up sampling blocks. Model was trained for 5 epochs using RMSprop optimizer with momentum. A combination of cross Entropy and dice score loss was used for making mask prediction.

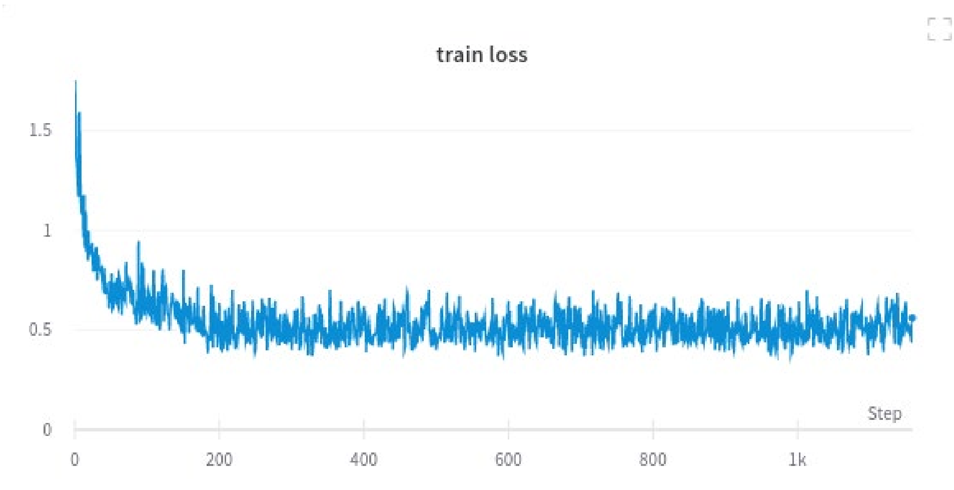


Figure 4: Train loss

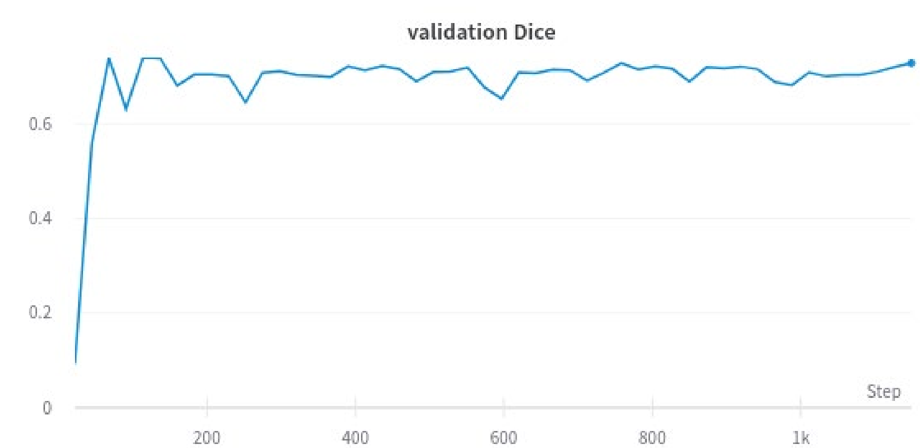


Figure 5: Validation dice loss

Results:

U-Net significantly out preforms classical methods and achieved a dice score of **0.78** after evaluating on whole test dataset.

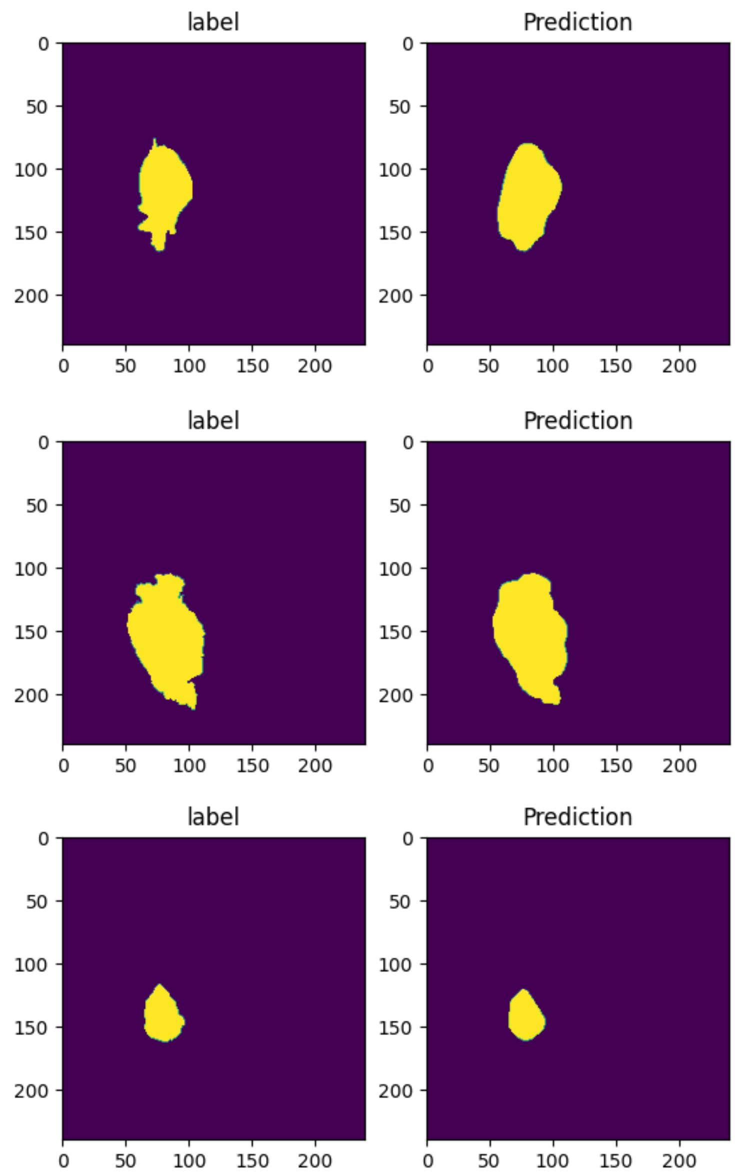


Figure 6: U-Net results

Conclusion:

In this assignment we have to apply different segmentation methods on the MRI dataset. It was found that for region growing and graph-cut segmentation map mainly rely on the input conditions. Seeding point and thresholding for region growing and scribbles for graph-cut. In case of deep learning-based U-Net model, we achieve consistent results. Following table summarizes the dice scores of these three methods.

Method	Dice Score
Region growing	0.65
Graph Cut	0.54
U-Net	0.78