Medical Ultrasound Nerve Segmentation Using Deep Learning

Guided by :- Dr. N. Srinivas Naik

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Dr. Shyama Prasad Mukherjee International Institute of Information Technology, Naya Raipur

Avinash Sharma (18100012)
Deewanshu Ukey (18100016)
Rahul Nagwanshi (18100044)

Introduction

- Surgery can cause persistent pain and short-term discomfort. Anesthesia is injected into patient’s body to reduce the pain.
- **Regional Anesthesia (RA)** is employed when the surgery involves a local procedure.
- This method is gaining wide attention because of its **non invasive nature**
- However, because of the characteristics of **high speckle noise** and **echo perturbations**, it is challenging to identify accurate location of the nerve and its structure around it.

Problem Statement

The development of a system for segmentation of nerve and identification of nerve structure using ultrasound images can aid the task of injecting anesthesia by avoiding any discrepancy.

Traditional Solution and its drawbacks

- During operations, it can be difficult for surgeons to avoid severing crucial nerves because they look so much like other tissue. A new noninvasive approach that uses **polarized light** to make nerves stand out from other tissue could help surgeons avoid accidentally injuring nerves or assist them in identifying nerves in need of repair.

- There are a few techniques available to help doctors identify nerves, but they have various limitations such as **not providing real-time information, requiring physical contact with the nerve or requiring the addition of a fluorescent dye.**

Literature Survey

1. **Ultrasound Nerve Segmentation of Brachial Plexus Based on Optimized ResU-Net -** median filtering is first employed to reduce the speckle noise followed by Dense Atrous Convolution (DAC) and Residual Multi-kernel Pooling (RMP) modules are integrated into the ResU-Net architecture to reduce the loss of spatial information.

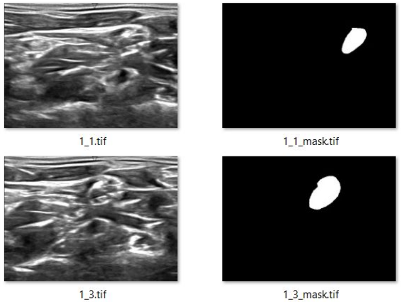
2. **Automatic Segmentation of Nerve Structures in Ultrasound Images Using Graph Cuts and Gaussian Processes -** using Graph Cut segmentation in order to generate regions of interest followed by a specific non-linear Wavelet transform is used for the feature extraction stage, and Gaussian processes for the classification step.

Literature Survey

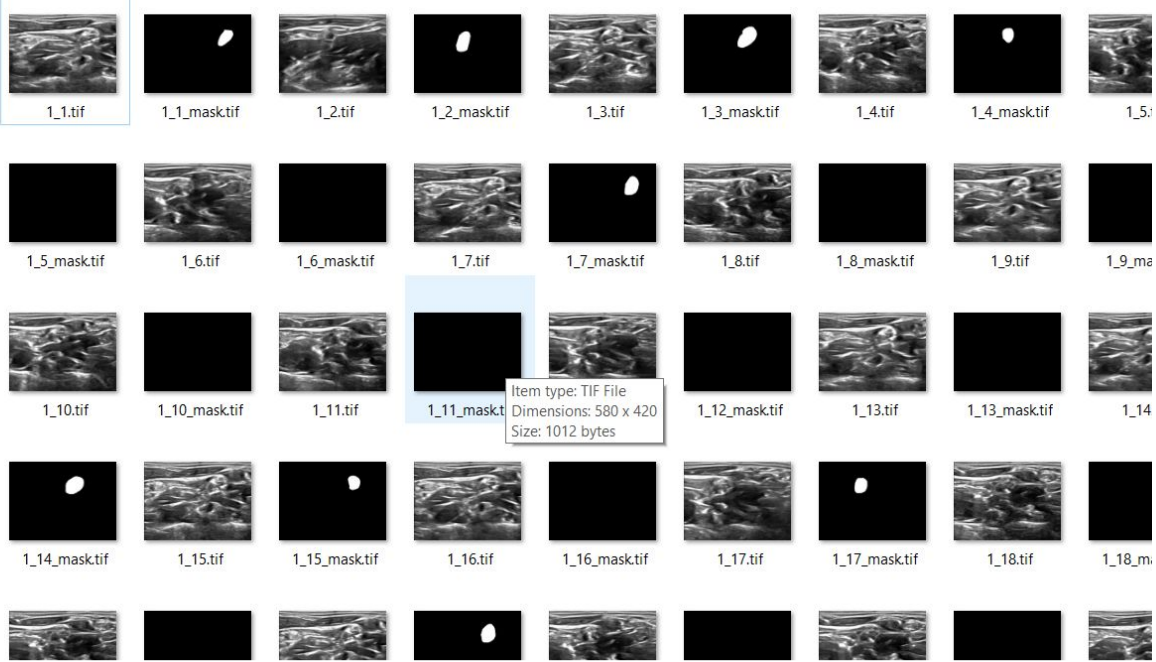
3. A probabilistic framework based on SLIC-Superpixel and Gaussian processes for segmenting nerves in ultrasound images - used Graph cuts segmentation to define a region of interest which were divided into several correlated regions using SLIC (Simple Linear Iterative Clustering)-superpixels, then, a nonlinear Wavelet transform followed by Gaussian Processes is applied.

Dataset Description

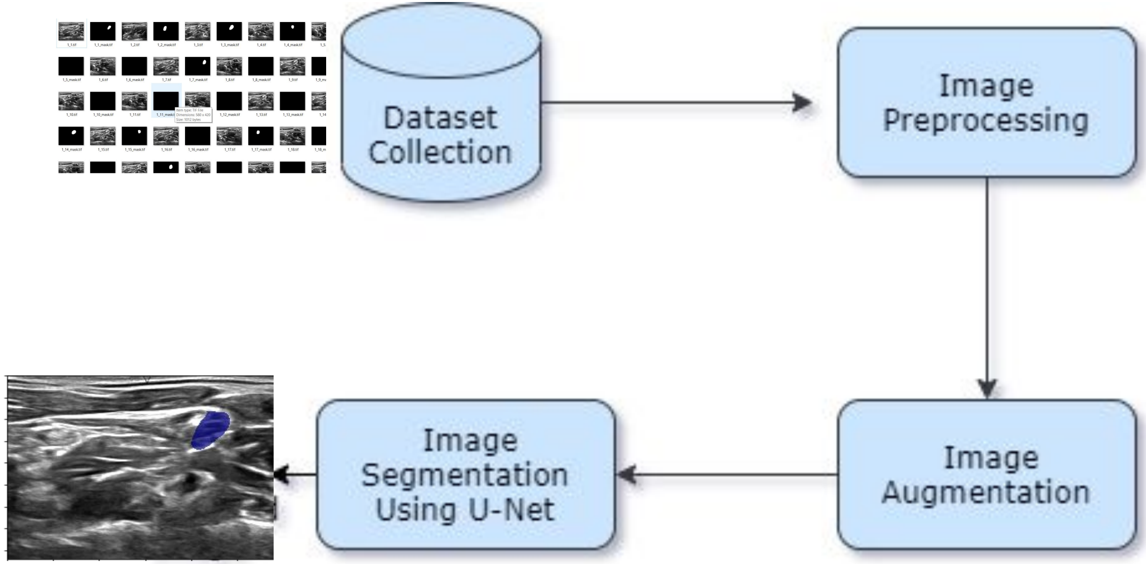
- The dataset used for training and testing the model was taken from **Halyard Health Nerve Dataset**.
- The dataset consisted of 16,778 high resolution images.
- The training dataset composed of Non-mask and Mask images.
  - -Sort the Non-mask images with its corresponding mask image
  - -Label the binary classes of the mask image.
- The testing data composed of Non-mask data for testing purpose.



Dataset Sample



Workflow



Segmented image

Image Preprocessing and Data Augmentation

- For preprocessing, we used basic functions like Rotation Range, width shift and height shift range, Sheer and Zoom range and flipping it horizontally with fill mode set to nearest.

- For Augmentation, we used flip and rotate methods for flipping in both the direction vertically and horizontally before moving to train the model.

Proposed Solution

- Modern Machine learning and Deep learning algorithms are far more advanced to perform complex tasks of Image segmentation, Image recognition and also performing tasks over the results obtained.
- Machine learning algorithms were quite inefficient in segmenting right nerve section from ultrasound images.
- Hence , we choose Deep learning for this task .In recent years, CNNs have demonstrated outstanding performance as feature extractors and classifiers in image recognition tasks such as the ImageNet challenge. Hence they prove right choice for such type of task.

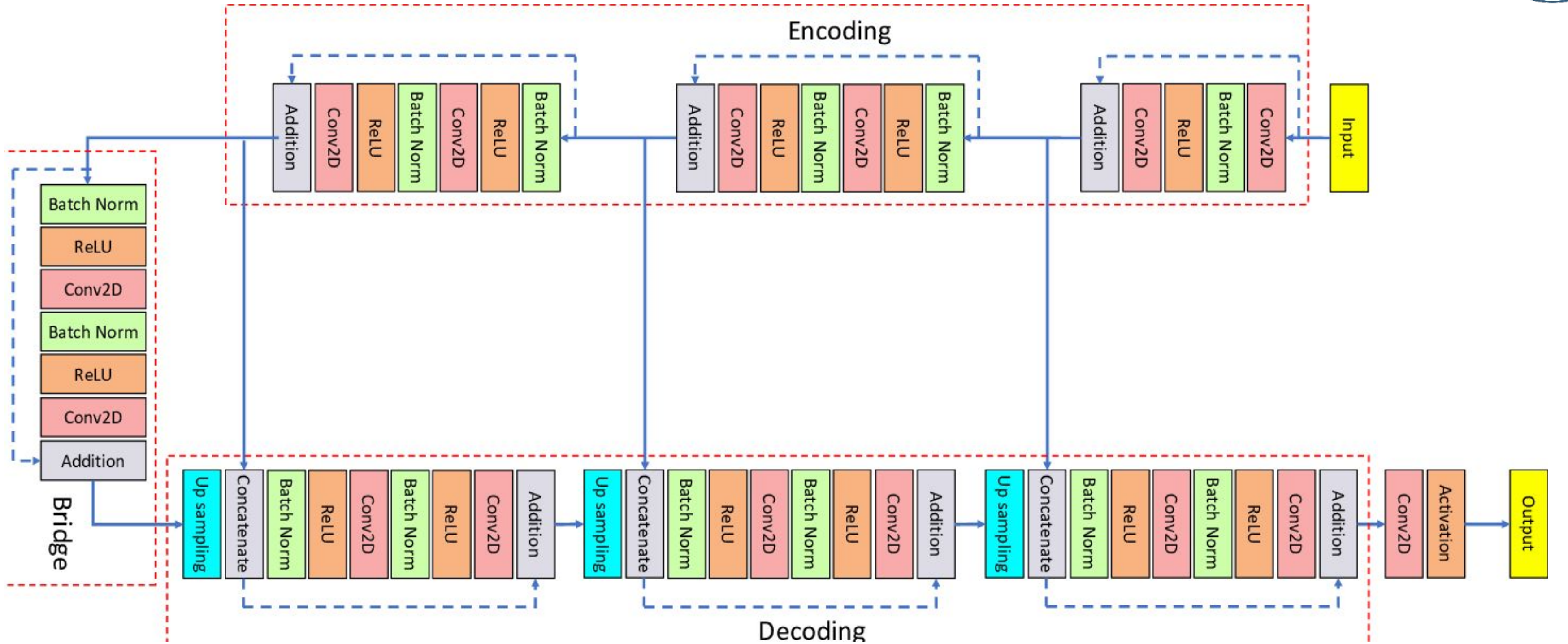
Proposed Solution

- Output of semantic segmentation is not just a class label or some bounding box parameters. In-fact the output is a complete high resolution image in which all the pixels are classified.
- Thus if we use a regular convolutional network with pooling layers and dense layers, we will lose the “WHERE” information and only retain the “WHAT” information which is not what we want. In case of segmentation we need both “WHAT” as well as “WHERE” information.

Proposed Solution

- Hence there is a need to up sample the image. In the literature, there are many techniques to up sample an image. Some of them are bi-linear interpolation, cubic interpolation, nearest neighbour interpolation, unpooling, transposed convolution, etc. However in most state of the art networks, transposed convolution is the preferred choice for up sampling an image.

UNet Architecture



Proposed Solution

- The Architecture contains two paths. First path is the contraction path (also called as the encoder) which is used to capture the context in the image. The encoder is just a traditional stack of convolutional and max pooling layers.
- The second path is the symmetric expanding path (also called as the decoder) which is used to enable precise localization using transposed convolutions. Thus it is an end-to-end fully convolutional network (FCN), i.e. it only contains Convolutional layers and does not contain any Dense layer because of which it can accept image of any size.

Methodology

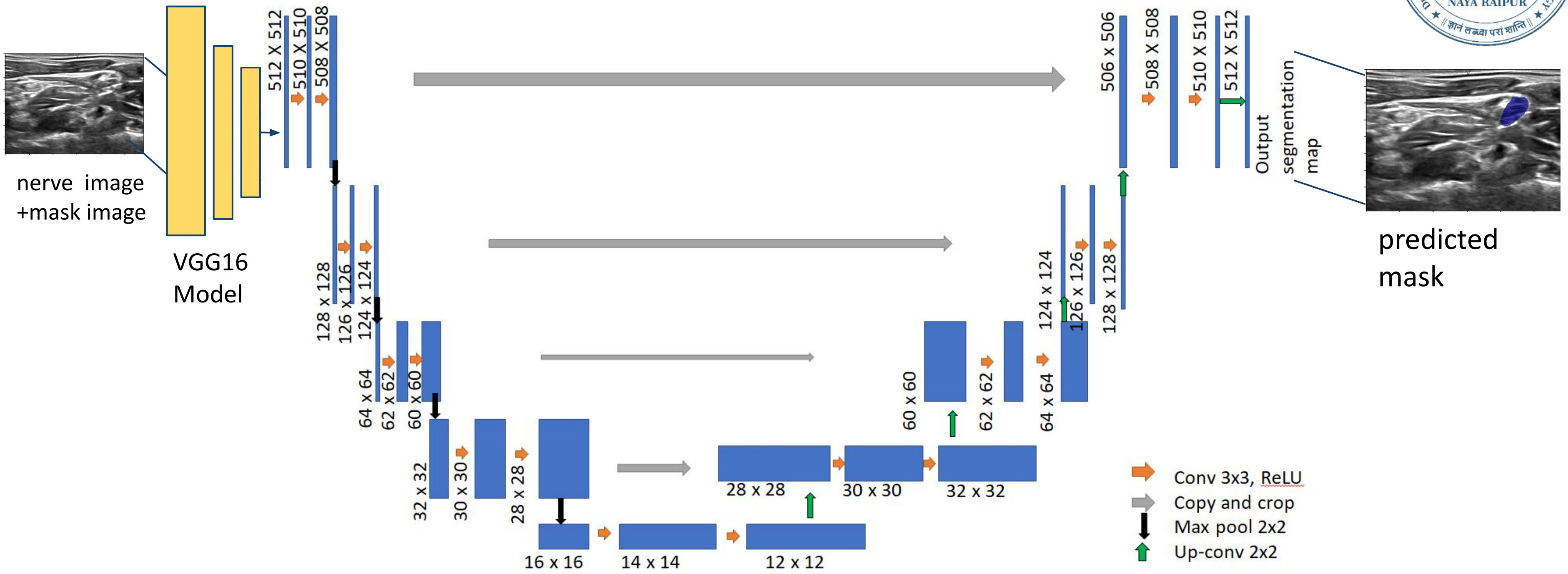


Fig. Architecture of UNet

Loss function: Dice Coefficient

- Since we are performing segmentation of medical images where borders aren’t clearly visible and there is always threat of class imbalance, so using cross entropy loss as loss function isn’t preferred for this task. hence, we used Dice coefficient as our loss function.
- Dice coefficient is essentially a measure of overlap between two samples. This measure ranges from 0 to 1.

Expected Results: Visualization

```
[23] # Display the first image and mask of the first subject.
     image1 = np.array(Image.open(path+"1_1.tif"))
     image1_mask = np.array(Image.open(path+"1_1_mask.tif"))
     image1_mask = np.ma.masked_where(image1_mask == 0, image1_mask)

     fig, ax = plt.subplots(1,3,figsize = (16,12))
     ax[0].imshow(image1, cmap = 'gray')

     ax[1].imshow(image1_mask, cmap = 'gray')

     ax[2].imshow(image1, cmap = 'gray', interpolation = 'none')
     ax[2].imshow(image1_mask, cmap = 'jet', interpolation = 'none', alpha = 0.7)
```

```
<matplotlib.image.AxesImage at 0x7f603f039e50>
```

Displaying the first image and mask of the first subject.

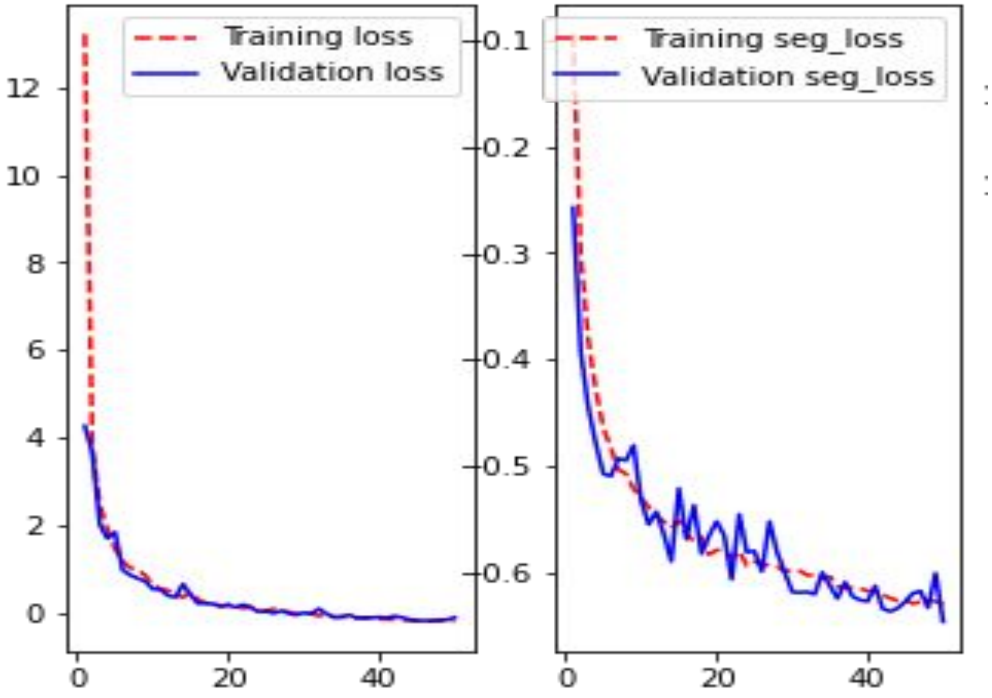
Results : Metrics

```
accuracies :  [0.98685634]
losses :  [-0.61818051]
ious :  [0.44776064]
dicecoefs :  [0.61818051]

average accuracy :  0.9868563413619995 +- 0.0
average loss :  -0.618180513381958 +- 0.0
average iou :  0.4477606415748596 +- 0.0
average dice_coe :  0.618180513381958 +- 0.0
```

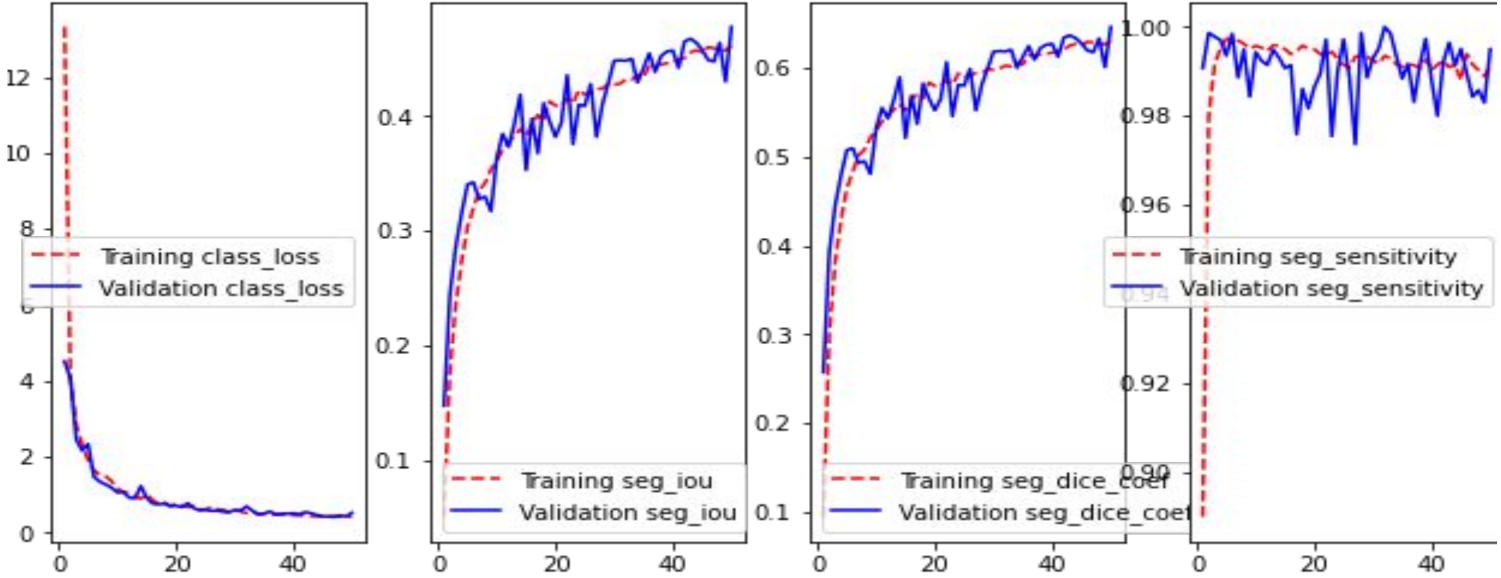
Accuracy	0.98
Loss	-0.61
ious	0.44
Dicecoeff	0.61

Results: K-fold cross validation



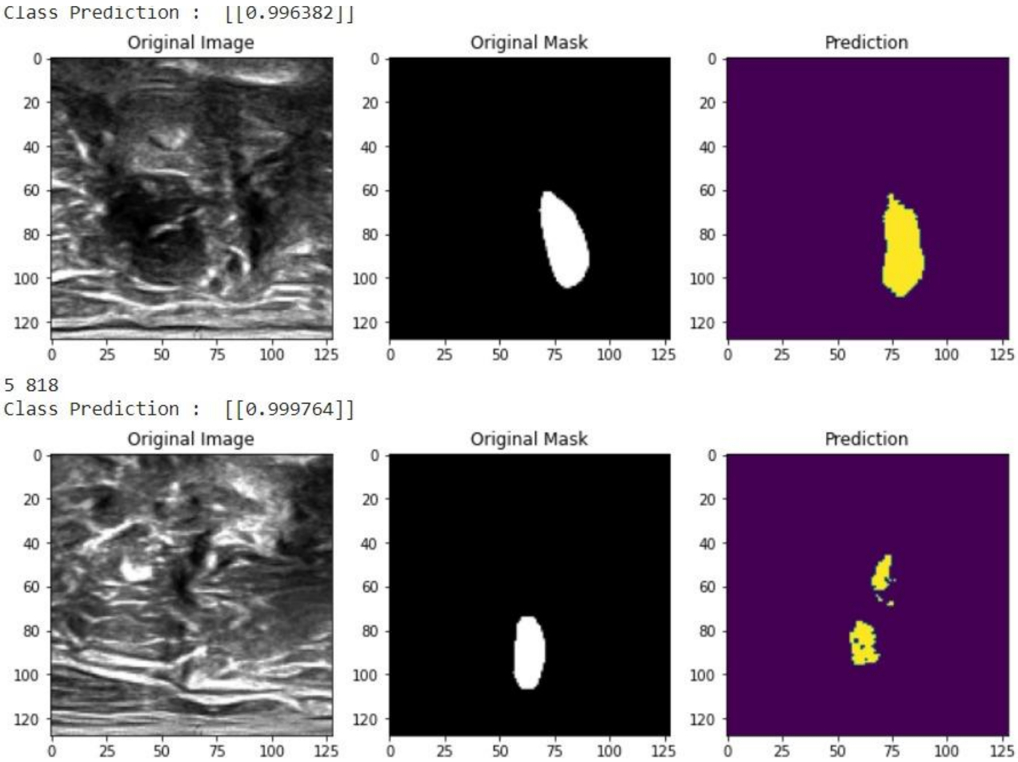
Observing both the validation curve and the training curve.

Results: K-fold cross validation



We can observe that with time, graph gets more better. accuracy getting better with fall of loss curve and same with IoU.

Predictions



Future Work :

- Segment performance may be boosted by using different architectures like ResU-Net, ResNet or RefineNet.

- In the future, we would like to use this method to other medical image segmentation like thyroid and breast tumor.

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Thank You

Dr. Shyama Prasad Mukherjee International Institute of Information Technology, Naya Raipur