A

VI Semester

MINOR PROJECT REPORT
ON

"MEDICAL ULTRASOUND NERVE SEGMENTATION USING DEEP LEARNING"

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Medical ultrasound Image nerve segmentation

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Dated: 10th May, 2021

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Rahul Nagwanshi

ABSTRACT

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. It involves injecting the anesthetic into the nerve block as close as possible to the nerve. Ultrasound guided regional anesthesia (UGRA) is the Regional Anesthesia technique of injecting the anesthetic in required amounts to immobilize the region to be covered, using ultrasound images of patients. This method is gaining wide attention because of its non invasive nature and it offers an accurate information of the nerve structure around it. 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 even by specialists. The development of a system for segmentation of nerve and identification of nerve structure using ultrasound images can aid this task by avoiding any discrepancy in providing anesthesia and hence eliminate any risk of severe damage to the respective region of the body or side effects to the rest of the body.

Keywords: Deep learning, Unet, Image Segmentation, Ultrasound, MRI.

Contents

List of Figures

Chapter 1

Introduction

Ultrasound has recently become one of the most common and popular medical technique, because of its economy-efficient, real-time and convenience. The accurate ultrasound nerve segment arose quite a lot of attention for its significance in regional anesthesia. Compared to the total anesthesia, the regional anesthesia is employed when the surgery involves only a local procedure, which can reduce the surgical injury and speed up the recovery of surgery. Regional anesthesia needs to inject the anesthetic in the nerve block as close as to the nerve as possible during which the accurate ultrasound nerve segmentation is very significant.

Regional anesthesia (RA) is one of the most frequently undertaken tasks in hospitals throughout the world to reduce or nullify the effect of the persistent pain in patients due to accidents or sickness. This is done by injecting the anesthetic in required amounts depending on the region to be covered in the specific region of the nerve structure. Regional anesthesia is different from general anesthesia in the sense, in general anesthesia the patient is unconscious throughout the operation, whereas in regional anesthesia only a particular area of the patient's body is made numb. Ultrasound guided regional anesthesia (UGRA) is one of the fields which is steadfastly growing in medical imaging presenting countless benefits due to the advances in ultrasound imaging technology. However, nerve identification still remains one of the most challenging tasks that the practitioners of regional anesthesia can face in the UGRA mechanism due to the low quality of the ultrasound images which are affected by the introduction of some artifacts (speckle noise) during the image capturing process and also since the nerve structure in the ultrasound images is not notable among others which further adds to the challenge. Also, any discrepancy in providing anesthesia can lead to severe damage to the respective region of the body or side effects to the rest of the body and also to the life of the patient, which further enhances the need for correctly identifying the right nerve region.

In the recent days, there are a number of effective semantic segmentation networks sprung up among them, the U-Net is popular and performs well in biomedical image segmentation for the following reasons. First, compared to the general images, the biomedical images are more semantic simple whose accurate segmentation needs more low level message which the U-Net architecture can offer. Second, lightweight networks like UNet are more suitable for the biomedical image segmentation for the sparse and treasure biomedical samples.

Chapter 2

Literature Survey

Before classifying and segmenting the Nerve images, we have performed literature survey to know about the existing methods which are already used for classification. One of the journal papers focused to quantify and analyze the factors responsible for the onset of wilt and its different stages.

[1] In this approach, a combination of deep convolutional neural network is used for obtaining features from several training images. Here the boosting algorithm is used for classification purposes. They Performed segmentation by leveraging the abstraction capabilities of convolutional neural networks (CNNs). They showed that learning-based segmentation method is robust, multi-region, exible and can be easily adapted to different modalities. In the attempt to show the capabilities and the behaviour of CNNs when they are applied to medical image analysis, they perform a systematic study of the performances of six different network architectures, proposed Hough-CNN, a patch-wise multi-atlas method which implicitly encodes priors on anatomic shape and context.The method is modality independent and scalable to multiple regions and harnesses the impressive classication power of CNNs and Deep Learning for application in clinical settings

[2]Shengfeng Liu a, Yi Wanga revies shows that from the perspective of image analysis, it is essential to develop advanced automatic US image analysis methods to assist in Ultrasound diagnosis and/or to make such assessment more objective and accurate. Deep learning has recently emerged as the leading machine learning tool in various research fields, and especially in general imaging analysis and computer vision. The review first briefly introduces several popular deep learning architectures, and then summarizes and thoroughly discusses their applications in various specific tasks in US image analysis, such as classification, detection, and segmentation. Finally, the open challenges and potential trends of the future application of deep learning in medical US image analysis has been discussed.

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Chapter 3

Proposed Model

During operations, it can be difficult for surgeons to avoid severing crucial nerves because they look so much like other tissue. so with the help of this simple model , we tried to segment the nerve from muscle fibre and tissues.Since machine learning algorithms proved less effective in segmentation of nerve images, so we proceeded with Deep learning model. We researched many Convolutional neural networks out of which we choose UNET with our own modifications for Semantic Segmentation of nerve images.

3.1 Architecture

A naive approach towards constructing a neural network architecture for this task is to simply stack a number of convolutional layers (with same padding to preserve dimensions) and output a final segmentation map. This directly learns a mapping from the input image to its corresponding segmentation through the successive transformation of feature mappings, however it's quite computationally expensive to preserve the full resolution throughout the network.

Also, in deep convolutional networks, earlier layers tend to learn low-level concepts while later layers develop more high-level (and specialized) feature mappings. In order to maintain expressiveness, we typically need to increase the number of feature maps (channels) as we get deeper in the network.

This didn't necessarily pose a problem for the task of image classification. Thus, we could alleviate computational burden by periodically downsampling our feature maps through pooling or strided convolutions (i.e. compressing the spatial resolution) without concern. However, for image segmentation, we would like our model to produce a full-resolution semantic prediction.

One popular approach for image segmentation models is to follow an encoder/decoder structure where we downsample the spatial resolution of the input, developing lower-resolution feature mappings which are learned to be highly efficient at discriminating between classes, and the upsample the feature representations into a full-resolution segmentation map.Hence , we needed an architecture that followed this structure which was fulfilled in UNet.

3.2 UNet

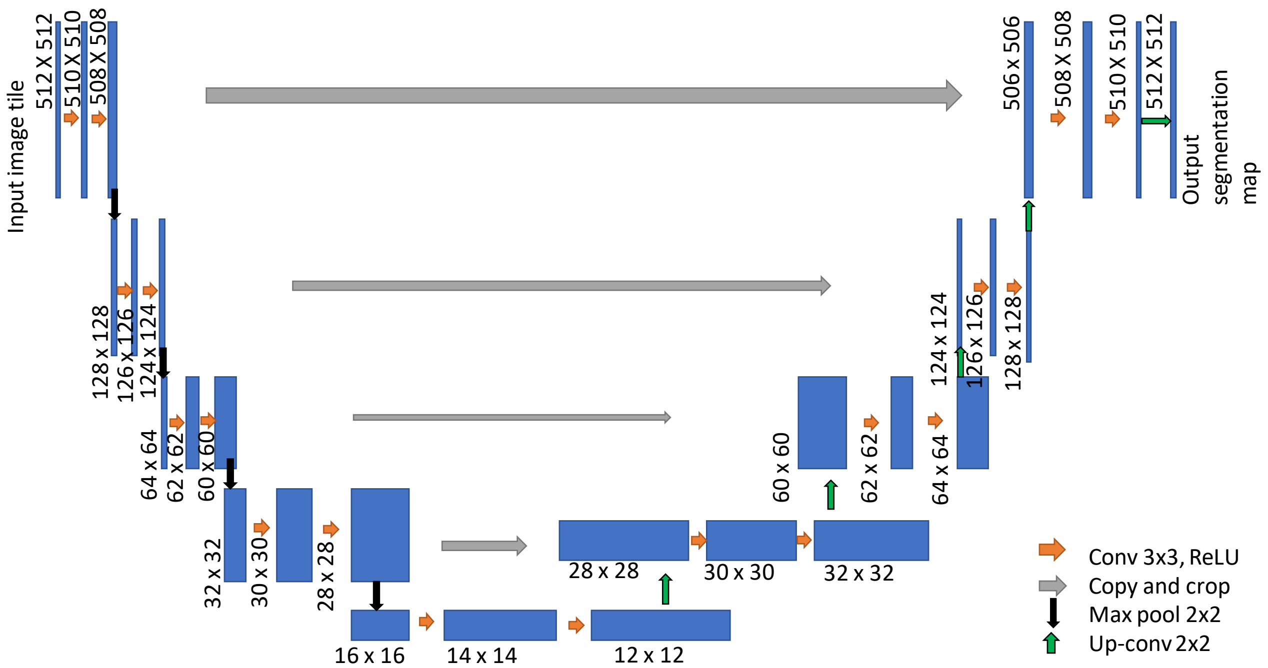

Figure 3.1: diagram of U-Net architecture

UNet, evolved from the traditional convolutional neural network, was first designed and applied in 2015 to process biomedical images.The reason it is able to localise and distinguish borders is by doing classification on every pixel, so the input and output share the same size.It has a “U” shape. The architecture is symmetric and consists of two major parts — the left part is called contracting path, which is constituted by the general convolutional process; the right part is expansive path, which is constituted by transposed 2d convolutional layers.

The encoder is the first half in the architecture diagram . It usually is a pretrained classification network like VGG/ResNet where we apply convolution blocks followed by a maxpool downsampling to encode the input image into feature representations at multiple different levels

The decoder is the second half of the architecture. The goal is to semantically project the discriminative features (lower resolution) learnt by the encoder onto the

```
conv_layer1 -> conv_layer2 -> max_pooling -> dropout(optional)
```

Figure 3.2: formula for encoding block of UNet

pixel space (higher resolution) to get a dense classification. The decoder consists of upsampling and concatenation followed by regular convolution operations.

```
conv_2d_transpose -> concatenate -> conv_layer1 -> conv_layer2
```

Figure 3.3: formula for decoding block of UNet

The main contribution of U-Net in this sense is that while upsampling in the network we are also concatenating the higher resolution feature maps from the encoder network with the upsampled features in order to better learn representations with following convolutions. Since upsampling is a sparse operation we need a good prior from earlier stages to better represent the localization.

In summary, unlike classification where the end result of the very deep network is the only important thing, semantic segmentation not only requires discrimination at pixel level but also a mechanism to project the discriminative features learnt at different stages of the encoder onto the pixel space . Hence UNet was quite effective for nerve segmentation from ultrasound images .

Chapter 4

Methodology

The entire process of development of the model is divided into several steps.These steps are explained in the following sections.

4.1 Dataset

The dataset used for training and testing the model was taken from Halyard Health Nerve Dataset[8]. The dataset consisted of 16,778 high resolution images. which is more than enough to train our model.

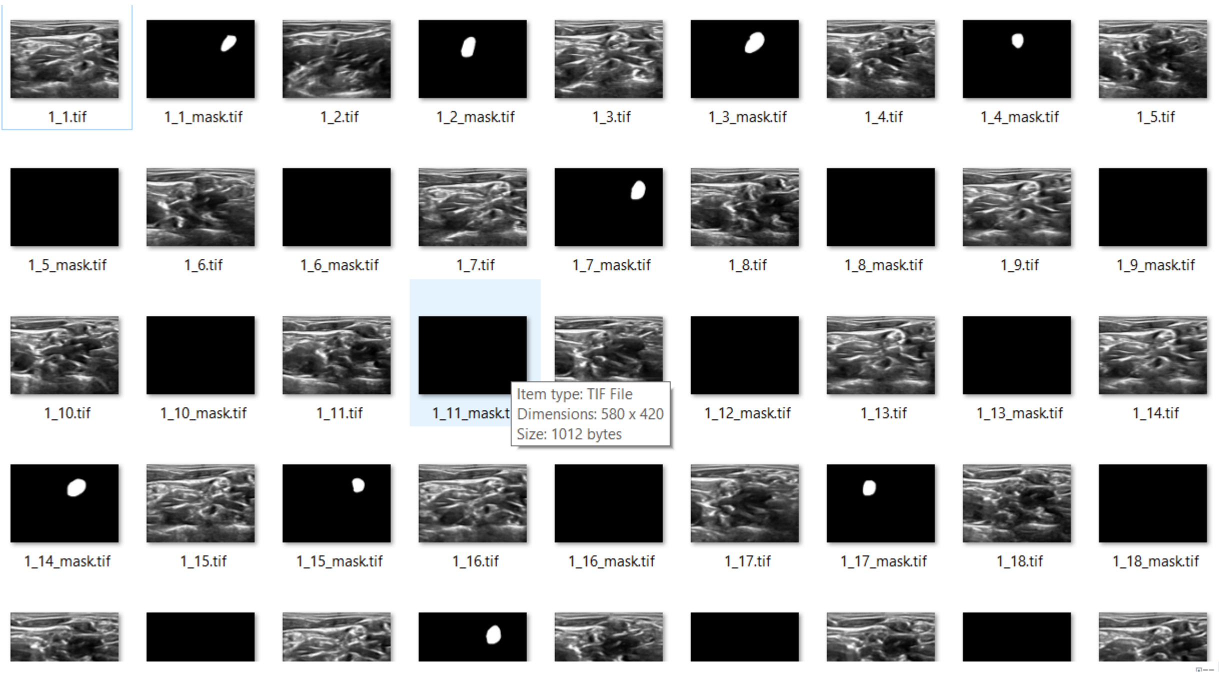

Figure 4.1: Samples of Dataset images

4.2 Dataset divisions

We have classified the Nerve Images into 2 major categories which are Mask and Non-mask images .

a. Mask images

b. Non-mask images

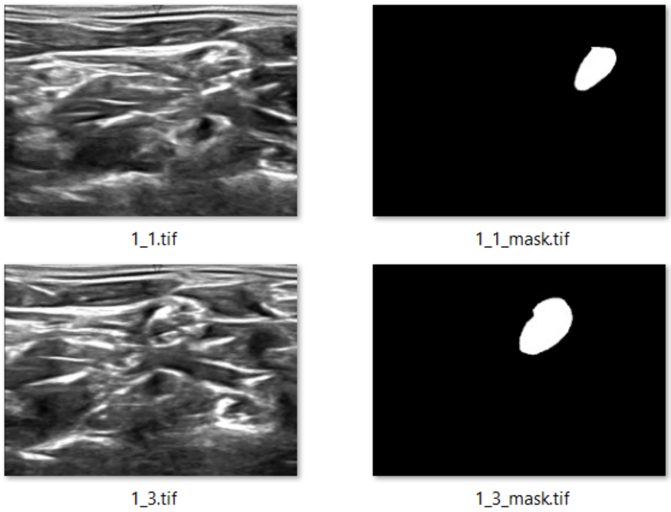

Figure 4.2: Non Mask and Mask images

Fig.[4.2] 1-3.tif shows the wide area ultrasound part of neck including nerves and 1-3-mask.tif shows the segmented part of neck where nerve is located.

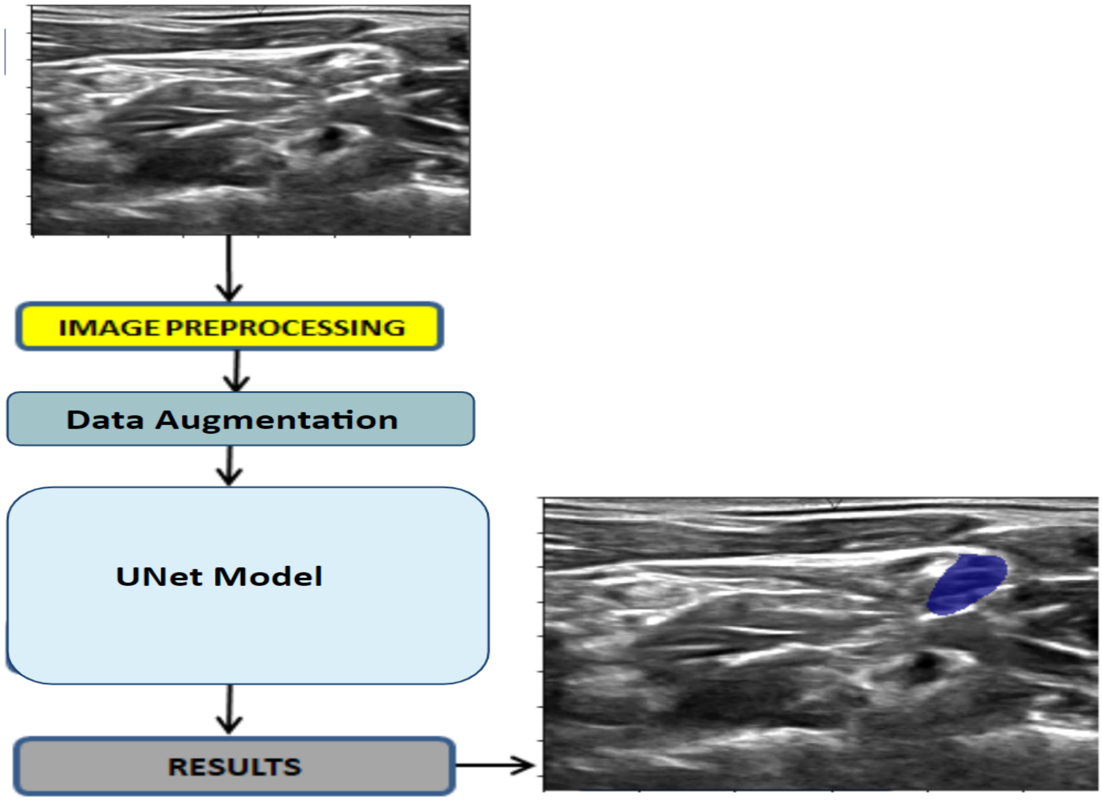

Figure 4.3: Proposed Model

4.3 Dice Coefficient for image segmentation

Since we are segmenting 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 where a Dice coefficient of 1 denotes perfect and complete overlap.

$$\text{Dice Coefficient} = \frac{2\text{xIntersection}}{\text{Union} + \text{Intersection}} = \frac{2TP}{2TP + FN + FP}$$

Figure 4.4: Dice coefficient calculation

our target mask is binary, we effectively zero-out any pixels from our prediction which are not "activated" in the target mask. For the remaining pixels, we are essentially penalizing low-confidence predictions; a higher value for the expression.

In order to formulate a loss function which can be minimized, we'll simply use 1-Dice. This loss function is known as the soft Dice loss because we directly use the predicted probabilities instead of threshold and converting them into a binary mask. A soft Dice loss is calculated for each class separately and then averaged to yield a final score.

Chapter 5

Results

Displaying the first image and mask of the first subject.

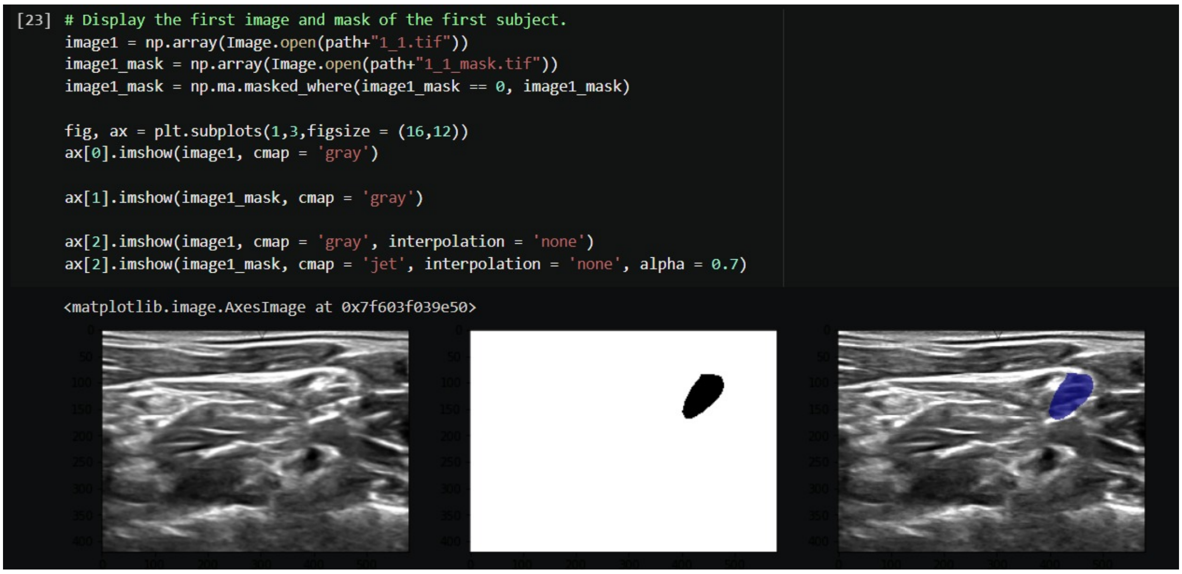

Figure 5.1: Displaying the first image and mask of the first subject.

Class prediction using Dice coefficient

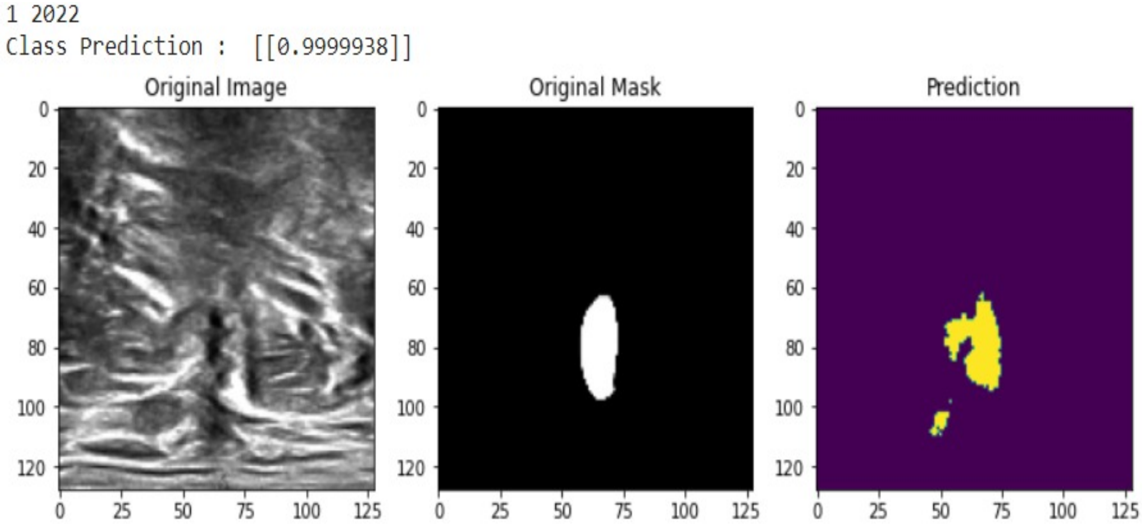

Figure 5.2: Class prediction 1

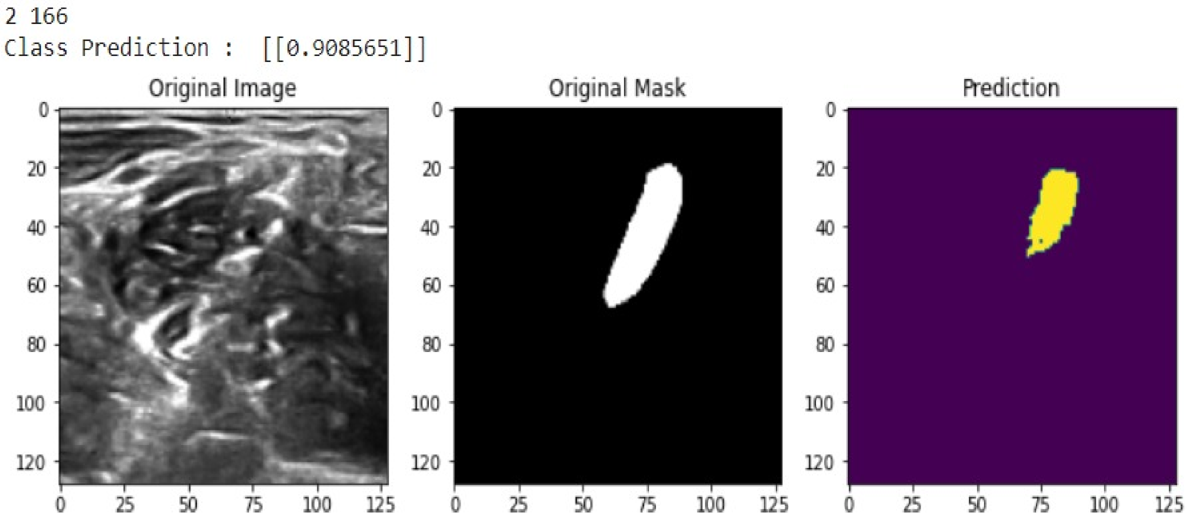

Figure 5.3: Class prediction 2

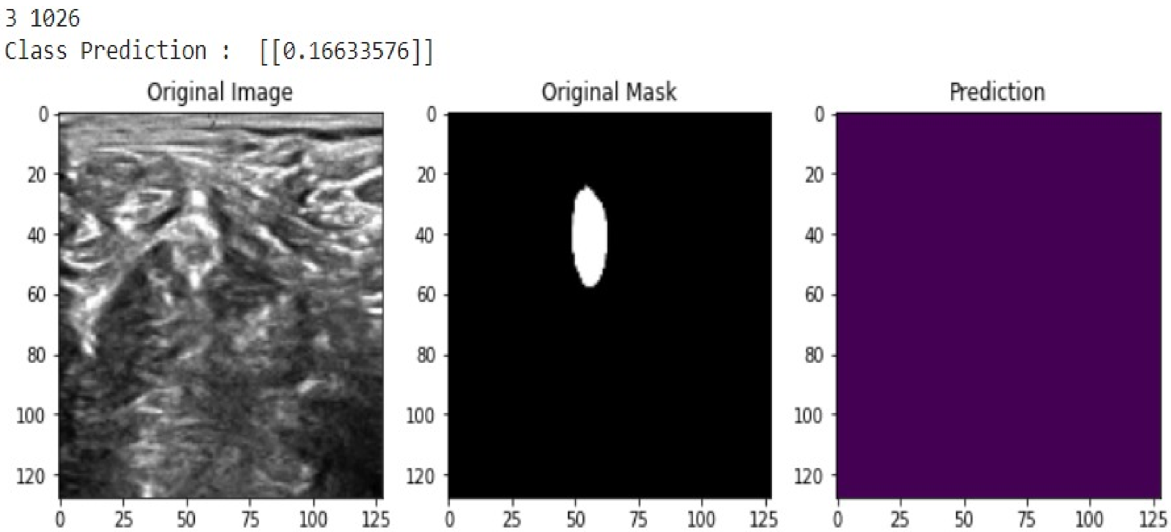

Figure 5.4: Class prediction 3

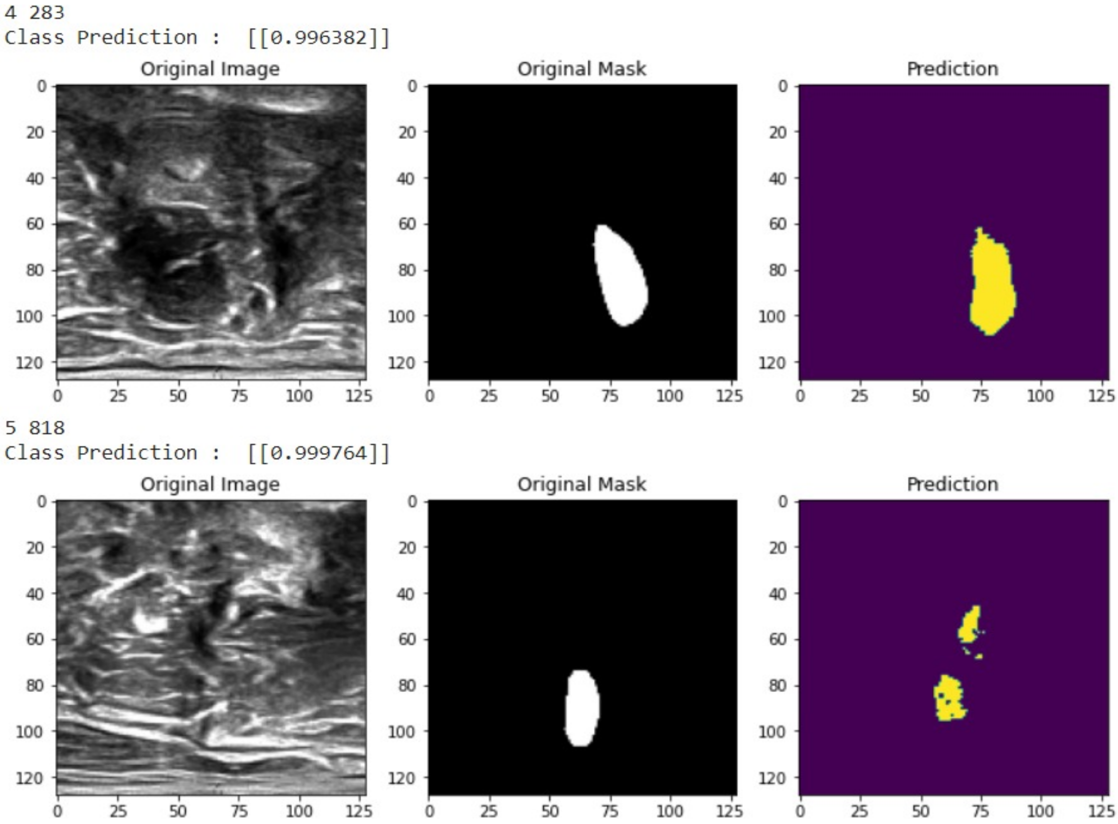

Figure 5.5: Class prediction 4 and 5

Above figure showed the prediction of our model along with true image.Its clear from above images that our model was successful in segmenting the nerve region from original images with good accuracy.

After running model for 50 epochs with 16,000 Datapoints, we achieved accuracy of 98.68%, with loss -0.61 and dice coefficient value of 0.6181

```
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
```

Figure 5.6: Accuracy achieved

The following figure shows average accuracy , average loss , average IoU score and average Dice coefficient value which agrees with good performance of our model Fig [5.6]

Accuracy	0.98
Loss	-0.61
ious	0.44
Dicecoeff	0.61

Figure 5.7: Accuracy Table

Following figures shows the K-Fold cross validation result.

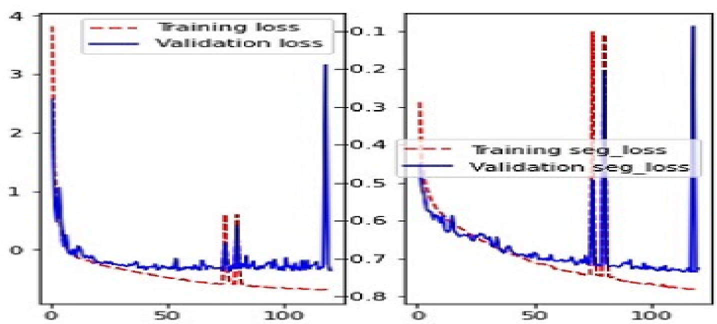

Figure 5.8: Loss and Seg-loss

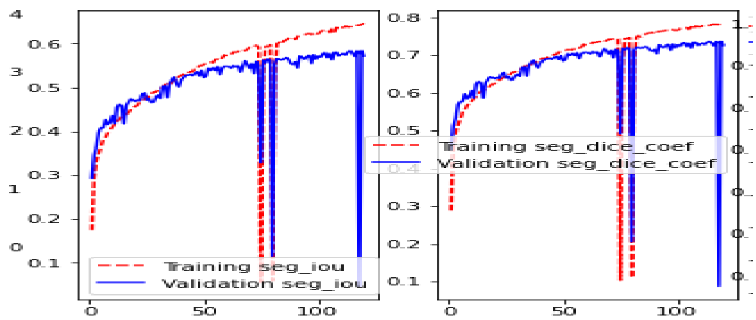

Figure 5.9: Seg-iou and Seg-dice-coefficient

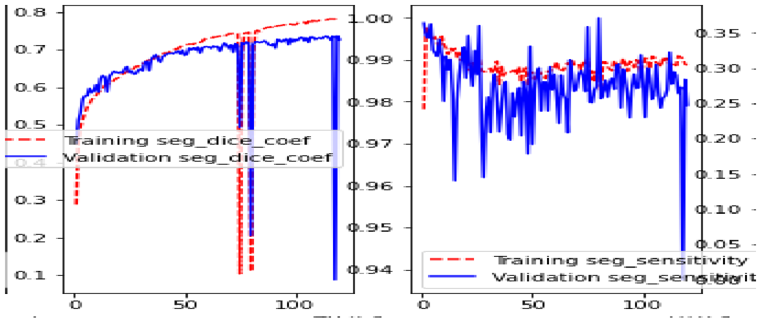

Figure 5.10: Seg-dice-coefficient and Seg-sensitivity

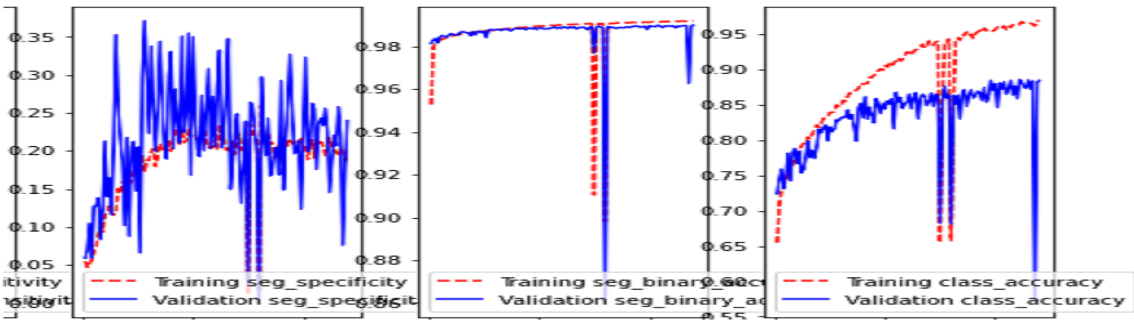

Figure 5.11: Seg-specificity, Seg-binary accuracy and Class Accuracy

Two curves are present in a validation curve – one for the training seg-dice coefficient and one for the validation seg-dice coefficient. we are getting both the validation loss curve and the training loss curve looking as similar as possible. by carefully observing K fold cross validation graph we can observe that with time graph gets more better, accuracy getting better with fall of loss curve respectively and same with IoU.Fig [5.9]

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

Ultrasound nerve segmentation has significant applicant value in regional anesthesia, reducing surgery injuries and speeding up the recovery of surgery. In the proposed paper, we developed a system for automatic end-to-end semantic segmentation of ultrasound nerve images with high speckle noise and echo perturbations based on deep learning algorithms. Our system predicts the masks with the location of the region which contain the Brachial Plexus nerve and the system predicts mask with black background for region in the images which do not contain the nerve. Compared with the basic U-Net model, our model preserve more spatial message by extracting effective and high level features and achieved an average accuracy of 98.68% with a Dice score of 0.6181. The system has a wide application in medical field. It will aid doctors to avoid any discrepancy in providing anesthesia, eliminating risk of severe damage to the respective region of the body or the side effects to the rest of the body without any human intervention.

6.2 Future Scope

In the future, we would like to use this method to other medical image segmentation like thyroid and breast tumor. Furthermore, others methods can be explored to improve the dice coefficient of the segmentation using superpixels which include more spatial message and exploiting Graph Cuts segmentation method. Also segmentation performance may be boosted by using different architectures like ResU-Net, ResNet or RefineNet.

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