Ultrasound Nerve Segmentation

Using UNET

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***Abstract*— The identification of nerve is difficult as structures of nerves are challenging to image and to detect in ultrasound images. Nevertheless, the nerve identification in ultrasound images is a crucial step to improve performance of regional anesthesia. In this paper, we introduce UNET Network to segment such tissues. Moreover, applying some metrics to validate our results, such as Dice and Jaccard indices. Quantitative experimental results show the proposed network can segment BP nerve from the ultrasound images with a good performance.**

Keywords— Brachial plexus segmentation, ultrasound image, deep learning, instance segmentation.

I. Introduction

Brachial plexus (BP) is a network (plexus) of nerves formed by the anterior rami of the lower four cervical nerves and first thoracic nerve. These nerves control the motions of your wrists, hands and arms, allowing you to raise your arm, type on your keyboard or throw a baseball. The brachial plexus nerves extend to the skin and are sensory, too. For instance, they let you know that the pan you just grabbed with your hand is too hot to hold. Currently, patient pain is frequently managed through the use of narcotics that bring a bevy of unwanted side effects. Pain management catheters reduce dependence on narcotics and speed up patient recovery. Accurately identifying nerve structures in ultrasound images is a critical step in effectively inserting a patient's pain management catheter. Our goal is to identify nerve structures in a dataset of ultrasound images of the neck.

II. Related Work

One of the proposed methods is a network called Brachial Plexus Multi-Instance Segmentation Network (BPMSegNet) which is proposed to identify different tissues (nerves, arteries, veins, muscles, etc.,.) in ultrasound images. The BPMSegNet has three novel modules. The first is the spatial local contrast feature, which computes contrast features at different scales. The second one is the self-attention gate, which reweighs the channels in feature maps by their importance. The third is the addition of a skip concatenation. Its strength is comparing to the Mask R-CNN and YOLACT, the proposed method shows the consistently stability and availability for both segmentation and detection tasks [1].

Another method demonstrates the possibility of detecting and segmenting the sciatic nerve structure, the method is based on Monogenic signal and probabilistic active contour approaches. Its strength is that it achieves 96% of F-score. On the other hand, its weakness is that CNN may generate non negligible rate of false positives among the detected ROIs due to the noise and different artefacts [2].

III. Dataset and Features

We have 11270 images of training set where the nerve has been manually annotated by humans, named according to subject_imageNum.tif. Every image with the same subject number comes from the same person. This folder also includes binary mask images showing the BP segmentations. Testing dataset contains 5508 testing images named according to imageNum.tif. There is no overlap between the subjects in the training and test sets. The vertical and horizontal resolutions of images are 96 dpi with 580 x 420 dimensions. Figures 1 and 2 show examples from the dataset.

This folder was uploaded on Google Drive as a zip file and it was unzipped and imported on the notebook using Google Colab.

For the preprocessing we will make all images have the same sizes and normalization.

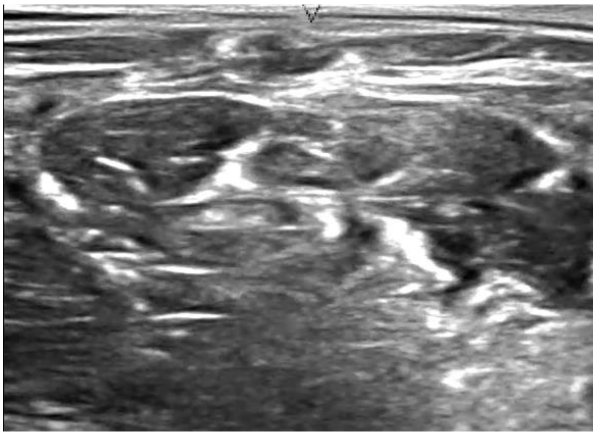

Figure 1 Example of Training Image

Figure 2 Mask showing Position of BP

IV. Methods

For training our model, we will be using U-NET Algorithm. U-NET augments the standard CNN architecture by adding a corresponding expansive path (aka the decoder) with the goal of producing a full-resolution semantic prediction. In other words, to generate segmentation images that highlight specific features and objects that were found in the image and it can accept image of any size.

A. *UNET Architecture*

It is an encoder network followed by a decoder network.

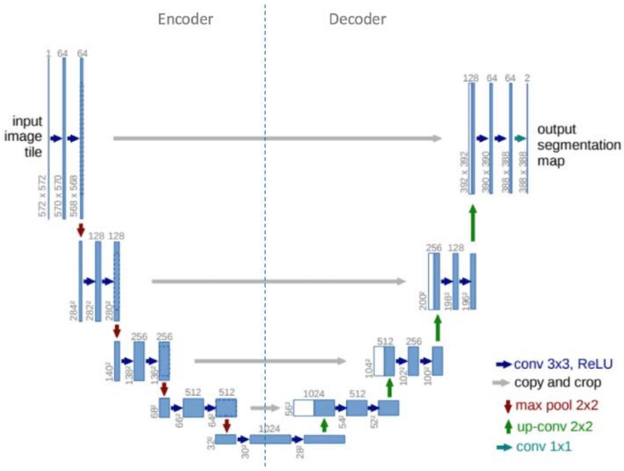

Figure 3 UNET Architecture

The encoder is the first half of figure 3. It is a pre-trained classification network. Convolution is applied followed by Maxpool down-sampling to encode the input image into feature representations at multiple different levels. More specifically, it consists of the repeated application of two 3x3 unpadded convolutions, each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for down-sampling. At each down-sampling step, the number of feature channels is doubled.

The decoder is the other half of figure 3. It consists of upsampling and concatenation followed by regular convolution operations. The goal is to semantically project the discriminative features (lower resolution) learnt by the encoder onto the pixel space (higher resolution) to get a dense classification. In detail, each step in the expanding path upsamples the feature map, followed by a 2x2 convolution (the transposed convolution). This transposed convolution halves the number of feature channels, while growing the height and width of the image. Next is a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. You need to perform cropping to handle the loss of border pixels in every convolution.

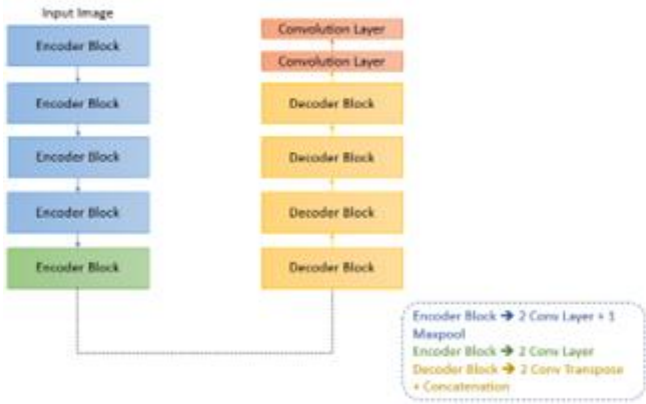

Figure 4 Block Diagram of UNET Architecture

Loss function used is categorical cross entropy function. This function is calculated as following:

$$Loss = -\sum_{i=1}^{output\ size} y_i \log \hat{y}_i$$

V. Experiments

A. *Hyperparameters*

Epochs are 20 epochs and 32 for batch size

B. *Optimizer*

Adam Optimizer is used because it is easy to implement, computationally efficient and requires little memory space. Furthermore, ultrasound images are noisy, Adam works well with noisy data and large datasets.

C. *Metrics*

- Jaccard Index

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

- Dice Index

$$D(A,B) = \frac{2|A \cap B|}{|A| + |B|}$$

- Accuracy

VI. Results

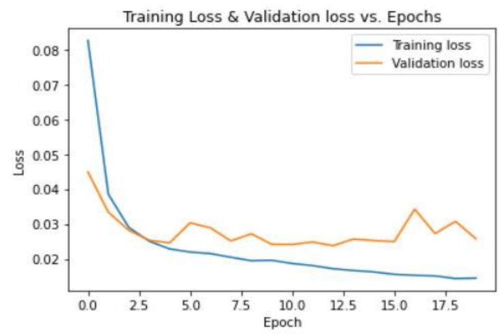

Figure 5 Training Loss and Validation Loss

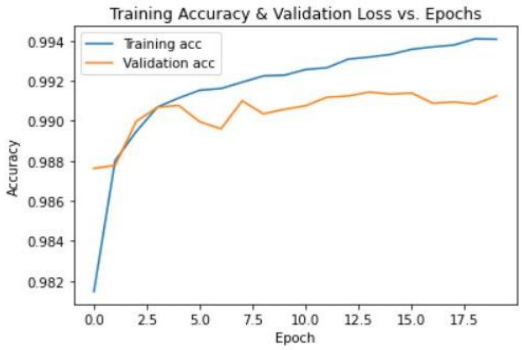

Figure 6 Training Accuracy and Validation Loss

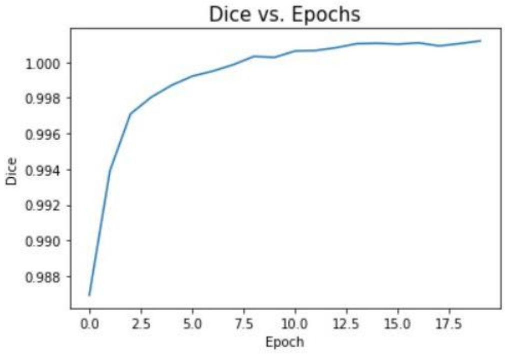

Figure 7 Dice Index

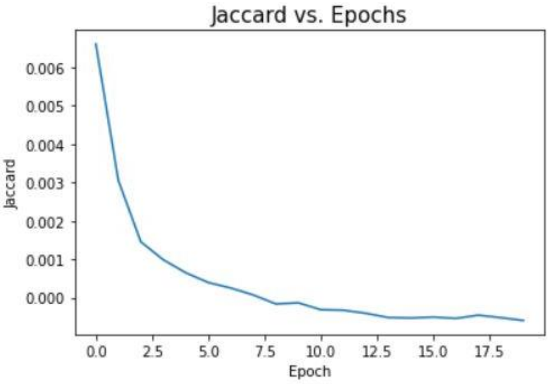

Figure 8 Jaccard Index

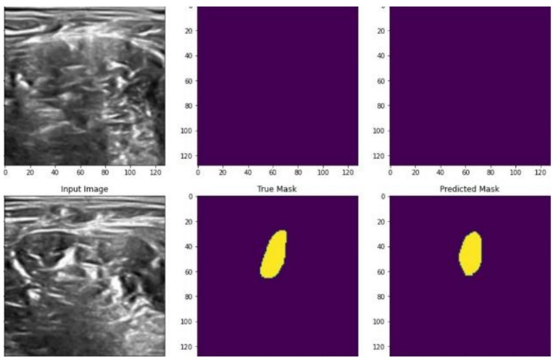

Figure 9 Validation

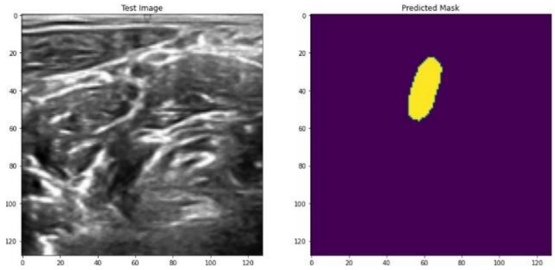

Figure 10 Predicted Mask

VII. DISSCUSIONS

Test Data is missing ground truth, so we do not have any quantitative results that make us confident about our results. We validated our algorithm using Validation Dataset as shown in Figure 9. Some of the results are giving wrong segmentation results or no segmentation at all.

VIII. CONCLUSION

In a nutshell, our problem was to segment the Brachial Plexus out of ultrasound images of the neck. We used UNET Model that we implemented using python, TensorFlow and Keras. We split the data into 20% validation and 80% training. The images were reshaped as a preprocessing step before training. We used metrics Jaccard, Dice Indices and Accuracy to assess the model. The results seemed promising and the accuracies were increasing.

IX. FUTURE WORK

For future work, training on different number of epochs and batch sizes and pick the most efficient numbers. We could experiment the accuracy of NAS-UNET in segmentation problems because it may achieve better accuracy [4].

CONTRIBUTION

Each member contributed with 25% of the project.

REFERENCES

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