SEGMENTATION OF NERVE STRUCTURES FROM ULTRASOUND IMAGES

A THESIS SUBMITTED TO THE

FACULTY OF ENGINEERING & TECHNOLOGY

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IN COMPUTER TECHNOLOGY

IN THE DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

SUBMITTED BY

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M.TECH IN COMPUTER TECHNOLOGY,6TH SEMESTER

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EXAMINATION ROLL NO.- M6TCT19011

REGISTRATION NO.-137106 OF 2016-17

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CERTIFICATE OF APPROVAL

This is to certify that ANSHUMALA RAKESH (Reg No.- 137106 OF 2016 - 17, Roll No.- 001610504003 & Examination Roll No.- M6TCT19011) has carried out her thesis work on her own for the partial requirement of M. Tech in Computer Technology under Computer Science & Engineering Department. This work is not submitted for any other degree. It is understood that, by this approval, the undersigned do not endorse or approve any statement made, opinions expressed or conclusions drawn therein, but approved the thesis for which it has been submitted.

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CERTIFICATE OF RECOMMENDATION

We hereby recommend that the thesis prepared by ANSHUMALA RAKESH (Reg No.- 137106 OF 2016 - 17, Roll No.- 001610504003 & Examination Roll No.- M6TCT19011) entitled "Segmentation of nerve structures in ultrasound images" be accepted as partial fulfillment of the requirements for the degree of Master of Technology in Computer Technology under the Computer Science & Engineering Department of Jadavpur University.

The thesis work undertaken in this dissertation is a result of candidate's own effort. The result embodied in this dissertation has not been submitted for any other degree.

1.-----------------------------------

(signature of the examiner)

2.-----------------------------------

(signature of the examiner)

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And finally, I would like to thank Jadavpur University, where I have done the final year project of the proposed Segmentation of nerve structure from ultrasound images, together with the preparation of this manuscript.

(signature)

Anshumala Rakesh

DECLARATION OF ORIGINALITY
AND
COMPLIANCE OF ACADEMIC ETHICS

I hereby declare that this thesis contains literature survey and original research work by the undersigned student, as part of the M. TECH IN COMPUTER TECHNOLOGY studies.

All information in this document have been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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SEGMENTATION OF NERVE STRUCTURES IN ULTRASOUND IMAGES

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ABSTRACT

The goal of this project is to segment the nerve structure namely (brachial plexus) in the ultrasound images (medical images).

We have gone through the previous research works and realized that they have used neural networks along with some machine learning algorithms. To proceed further, we went through some of the textbooks and even websites to first understand the structure of the nerve structure i . e. brachial plexus.

In this project, we have tried to segment the nerve structure from ultrasound images without using neural networks or any other algorithms that has been used previously.

In this project, we take an input image, which is a grayscale image of size 580*420, compute its histogram to analyze the input image, pre-process it using histogram equalization and filtering algorithms, apply thresholding algorithm to it, extract the required region which is containing the region of interest based on the structural properties of the input image, and finally apply the needed morphological operations to get the final output.

If the input image is containing the nerve structure, then it's output will be a binary image, where the region of interest will be indicated by the ‘white' pixels, using our proposed algorithm. If the image does not contain the nerve structure, then it will simply give a full ‘black' output, showing the absence of the nerve structure.

We have given more importance to the structural properties of the original image like area, Euler number, Eccentricity and etc. Because although all are grayscale images having the same size but they differ in their shapes of their region of interest. Images of a certain subset possess certain structural properties for region of interest.

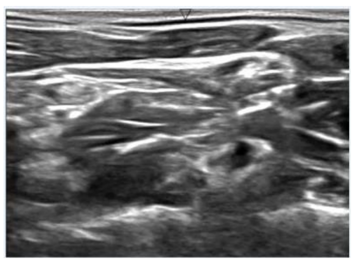
First of all, we made sure that each image having similar shape lie under the same class, then based on that, additional conditions were put first to extract the required region and then to extract the exact location of the region of interest.

The database is divided into a total of 47 subsets and images of each subset vary from that of another subset in its shape and structural properties, and hence, the images have been distinguished accordingly based on these properties.

INTRODUCTION

- ## IMAGE SEGMENTATION

Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. Accurately identifying the nerve structures, also called the Brachial Plexus, in the ultrasound images of the region around the neck can be modeled as an image segmentation problem [ref. Wikipedia].



(Fig.1) (a.) The Brachial plexus in a gray-scale image (b) its exact location in a binary image

- ## BRACHIAL PLEXUS

1. DEFINITION

Brachial means "pertaining to the arm", and A **plexus** (from the Latin for "braid") is a branching network of the vessels or nerves.

2. BRACHIAL PLEXUS IN A NUTSHELL

- The brachial plexus is a complex intercommunicating network of nerves formed by spinal nerves **C5, C6, C7, C8 and T1**.
- It supplies all **sensory innervation** to the **upper limb** and most of the **axilla**, with the exception of an area of the medial upper arm and axilla, which is supplied by the intercostobrachial nerve T2.
- It supplies all **motor innervation** to the muscles of the **upper limb** and **shoulder girdle**, with the exception of the trapezius, which is supplied by the spinal accessory nerve IX.
- It also supplies **autonomic innervation** to the upper limb by intercommunicating with the stellate ganglion of the

sympathetic trunk at the level of **T1**, where it gains sympathetic fibers which supply specialist functions:

- **Vasomotor** – stimulates **vasoconstriction** of arteries, arterioles and capillaries resulting in skin pallor and coldness
- **Pilomotor** – stimulates **contraction of arrector pili muscles** within hair follicles, making hairs stand on end
- **Sudomotor** or **secretomotor** – stimulates the **production of sweat** from sweat glands

▪ The brachial plexus begins as the **anterior rami** of five **spinal nerve roots C5-T1**, which emerge from the intervertebral foramen of their respective vertebrae to lie in the posterior triangle of the neck between the anterior and medial scalene muscles.

▪ The five spinal nerves quickly unite to form **superior**, **middle** and **inferior trunks**, which continue to pass laterally between the **anterior** and **medial scalene muscles** and cross the base of the **posterior triangle of the neck**, where they can be found **behind the subclavian artery**. They pass over the **apex of the lung** and the **first rib** towards the clavicle.

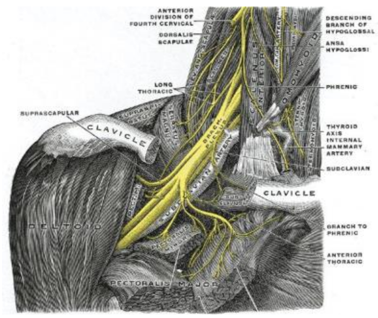
▪ **Behind the middle third of the clavicle**, each trunk splits into an **anterior division** and a **posterior division**. These continue to pass downwards behind the clavicle to enter the axilla.

▪ The six divisions combine to form **lateral**, **posterior** and **medial cords**. These are distributed around and named according to their relationship with the **second part of the axillary artery**, which is located behind the pectoralis minor muscle. The cords travel laterally with the axillary artery towards the arm. The artery and cords are en-sheathed by an extension of the prevertebral fascia known as the axillary sheath – this is a target for brachial plexus nerve blocks.

▪ The cords divide around the **third part of the axillary artery** into their **five terminal branches**: the **musculocutaneous**, **axillary**, **radial**, **median** and **ulnar nerves**.

▪ The brachial plexus gets its **blood supply** from various branches of the **subclavian artery** along its length, including:

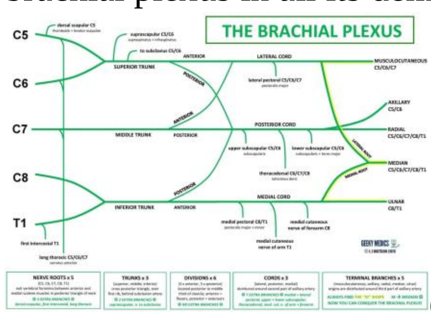
- **ROOTS:** vertebral artery, anterior and posterior spinal arteries
- **TRUNKS + DIVISIONS:** ascending and deep cervical arteries, superior intercostal artery
- **CORDS:** axillary artery



(fig.2) Brachial plexus shown in the yellow color.

3. STRUCTURE OF THE BRACHIAL PLEXUS

The diagram below summarizes the **structure** and **branches** of the brachial plexus in all its demoralizing glory.



(Fig.3) Structure of the Brachial Plexus

- **ROOTS –** There are **five nerve roots** from **C5-T1**, which give **three nerve branches**:
  - The **dorsal scapular nerve**
  - The **long thoracic nerve**
  - The **first intercostal nerve**.
- **TRUNKS –** The five nerve roots combine to form **three trunks:**
  - The **superior trunk** is formed from **C5** and **C6**
  - The **middle trunk** is formed from **C7**
  - The **inferior trunk** is formed from **C8** and **T1**
  - The **superior trunk** gives rise to **two nerve branches**: the **suprascapular nerve** and the **nerve to subclavius**. The

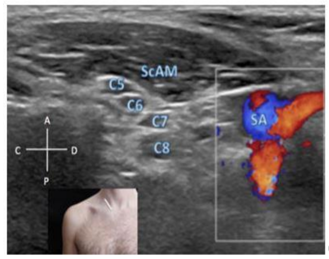
middle and **inferior trunks** do not give off any extra branches.

- **DIVISIONS –** There are **six divisions** in total, comprising of an **anterior division** and a **posterior division** from each of the three trunks:
    - **Anterior division fibers** usually supply **flexor muscles**
    - **Posterior division fibers** usually supply **extensors**
- **CORDS –**The divisions combine to form **three cords**, which are distributed around the **axillary artery:**
    - **The lateral cord** is formed from the **anterior divisions** of the **superior** and **middle trunks**. It gives **one extra nerve branch**: the **lateral pectoral nerve**.
    - **The posterior cord** is formed from the **posterior divisions** of the **superior**, **middle** and **inferior trunks**. It gives **three nerve branches**: the **upper subscapular nerve**, the **thoracodorsal nerve** and the **lower subscapular nerve**.
    - **The medial cord** is formed from the **anterior division** of the **inferior trunk**. It gives **three nerve branches**: the **medial pectoral nerve**, the **medial cutaneous nerve of the arm** (also known as the medial brachial cutaneous nerve) and the **medial cutaneous nerve of the forearm** (also known as the medial antebrachial cutaneous nerve).
- **TERMINAL BRANCHES –** The three cords branch to form **five terminal nerve branches** which supply the upper limb:
    - The **lateral cord** gives rise to the **musculocutaneous nerve** and the **lateral root of the median nerve**
    - The **posterior cord** gives rise to the **axillary nerve** and the **radial nerve**
    - The **medial cord** gives rise to the **medial root of the median nerve** and the **ulnar nerve [ref. B. D. Chaurasia]**

4. ULTRASOUND APPROACHES TO THE BRACHIAL PLEXUS

- ROOTS

In the sagittal oblique view, the emerging roots are seen as ovoid hypo-echoic images interposed between the anterior and middle scaleni muscles. The C8 root is located just posterior and slightly superior to the subclavian artery.

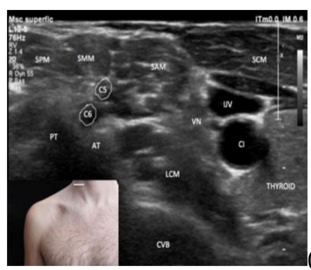


(Fig.4)

Roots of the brachial plexus-sagittal oblique view. A: anterior. C: cranial.C4: C4 spinal root. C5: C5 spinal root. C6: C6 spinal root.C7: C7 spinal root.C8: C8 spinal root. D: distal. M: medial. P: posterior.SA: subclavian artery.

- TRUNKS

In the axial plane, the three trunks of the brachial plexus can be seen between the anterior and middle scalene muscle, always in the inter-scalene triangle area, in continuity with the spinal rami.

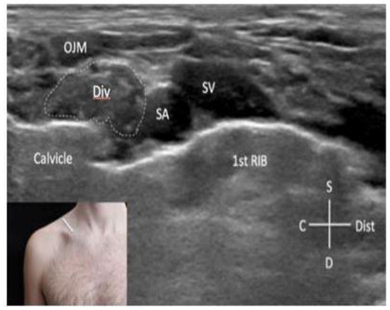


(Fig.5)

Trunks of the brachial plexus formation – axial view. AT: anterior tubercle. C5: C5 spinal root. C6: C6 spinal root. CVB: cervical vertebral body. IJV: internal jugular vein. LCM: longus colli muscle. SAM: scalene anterior muscle. SMM: scalenus medius muscle. SPM: scalenus posterior muscle. SCM: sternocleidomastoid muscle. PT: posterior tubercle. VN: vagus nerve.

- DIVISIONS

The divisions of the brachial plexus can be found at the lateral third of the supraclavicular fossa by a sagittal oblique slice, perpendicular to the main axis of the subclavian artery. A cluster of hypo-echoic fascicles corresponding to the six divisions of the brachial plexus is located just behind the subclavian artery.

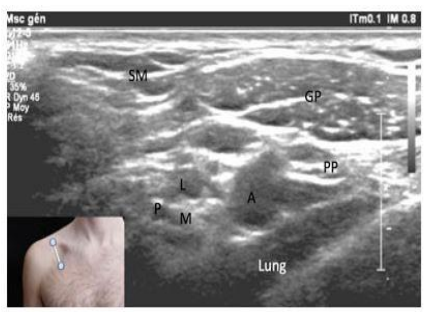


(fig.6)

Divisions of the brachial plexus. C: cranial. D: deep. Div.: divisions of the brachial plexus. Dis: distal. OJM: omohyoid muscle. SA: subclavian artery. SV: subclavian vein. S: superficial.

- CORDS

  The cords of the brachial plexus form a triangular hypo-echoic image located just above the subclavian artery: the posterior cord is located at the upper part of the triangle, the lateral cord is visible at the anterior and inferior part of the triangle, while posterior and inferior part of the triangle corresponds to the posterior cord.

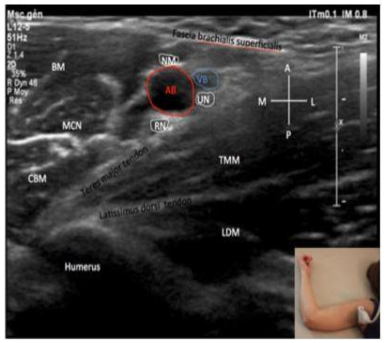


(Fig.7)

Cords of the brachial plexus – infraclavicular view. CA: subclavian artery. CV: subclavian vein. M: medial cord. L: lateral cord. P: posterior cord.GP: pectoral major muscle. PP: pectoralis minor muscle.

- BRANCHES

  The median nerve is located anterior to the artery, while the ulnar nerve is visualized between the axillary artery and the veins on the same view. The radial nerve can be found just posterior to the axillary artery. Two branches of the brachial plexus are placed far from the axillary vessel [ref. Radiopedia].



(fig.8)

Branches of the brachial plexus – branches other than the axillary nerve – axillary approach. A: anterior. AB: Brachial artery. BM: Brachialis muscle. CBM: coracobrachialis muscle. L: lateral. LDM: Latissimus dorsi muscle. NM: Median nerve. M: medial. MCN: musculocutaneous nerve. P: posterior. RN: radial nerve. TMM: UN: ulnar nerve. VB: brachial veins.

- WHY SEGMENTATION OF BRACHIAL PLEXUS IS NECESSARY?

  Pain is one of the most important aspects, that has to be properly managed, for easing the suffering of a patient and improve their quality of life. Pain management is typically done through the administration of narcotics, which also bring with them other unwanted effects. On the other hand, introducing pain management catheters, that block or mitigate the pain at source, reduce dependency on the narcotics and speed up the recovery process. The segmentation of Brachial Plexus is done so that the indwelling catheters are rightly placed and provide a pain-free future [ref. Segmentation of nerve structure in ultrasound images by Manikanta D Reddy].

- WHAT IS OUR RESEARCH OBJECTIVE?

  We need to design an algorithm such that when an ultrasound image is being provided as the input, it firstly determines, if that image contains the BRACHIAL PLEXUS or not, and if that image does contain the BRACHIAL PLEXUS, then show the exact location where it is present as the output. The input is a gray-scale image and the output will be a binary image. Our result will be compared with the already-given ground-truths to check the efficiency.

- HOW IT CAN BE DONE?

  This can be done by analyzing the structure of the Brachial Plexus and using the proper image processing methods for firstly filtering the input image, then analyzing the image, then applying the proper thresholding algorithm then applying certain properties to extract the region and then applying the proper morphological operations for getting the final output.

REVIEW OF LITERATURE

- PREVIOUS RESEARCH WORKS
  - **Automatic segmentation of nerve structures in ultrasound images using Graph Cuts and Gaussian processes.**

    Gil González J, et. Al. conf proc IEEE med biol soc.2015.

    In this paper, an initial step was carried out using Graph Cut segmentation in order to generate regions of interest; then they used machine learning techniques with the aim of segmenting the nerve structure; here, a specific non-linear Wavelet transform was used for the feature extraction stage, and Gaussian processes for the classification step. The methodology performance was measured in terms of accuracy and the dice coefficient.

  - **Segmentation of nerve structures in ultrasound images.**

    D Manikanta Reddy KAGGLE competition, November 2016

    In this paper, a method based on proposals by overlapping windows and the other based on U-net architecture was discussed. They also looked into the matter as to how the choice of architecture of the neural net, makes the learning different in the deeper layers. The results are computed by taking the mean of Dice Score of the predicted masks with the annotated masks.

  - **Segmentation of nerves on ultrasound images using a deep adversarial network.**

    CONG LIU, et. Al. conf proc IJICIC Feb 2018

    In this paper, they developed a deep adversarial neural network by firstly setting up a segmentation network based on well-established deep neural networks, then secondly, the anatomical dependencies were ensured by a discriminator network that assessed the segmentation quality and punished the segmentation network accordingly. And thirdly, the elastic deformation and its byproduct were handled by deformation data augmentation and diluted convolutions respectively.

- **Nerve structure segmentation from ultrasound images using random under-sampling and an SVM Classifier**

  C. Jimenez, et. Al. conf proc ICIAR 6 June 2018

  They proposed an approach based on random under sampling (RUS) and a support vector machine (SVM) classifier. They used a Graph Cuts-based technique to define a region of interest (ROI). Then, such an ROI was split into several correlated areas (super pixels) using the Simple Linear Iterative Clustering algorithm. Further, a nonlinear Wavelet transform was applied to extract relevant features. Afterward, they used a classification scheme based on RUS and SVM to predict the label of each parametrized super pixel. Their approach could deal with the imbalance issues when classifying a super pixel as nerve or non-nerve. Results showed that their method outperformed similar works regarding both the dice segmentation coefficient and the geometric mean-based classification assessment.

- SUMMARY OF THE LITERATURE REVIEW

  All the previous works were done using Neural Network and Machine learning algorithms. Some of them had used Graph cuts and gaussian processes and some of them had used sliding window mechanism. Some of them had also used random under-sampling. The results were compared using their dice coefficient.

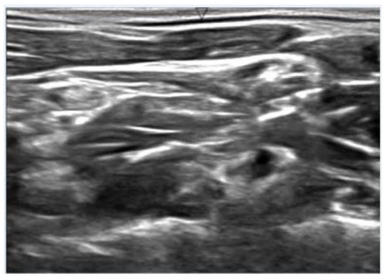
- RESEARCH OUTPUT

  All the research papers that I went through have dealt with the segmentation using Neural Networks or other Machine Learning Algorithm. In this paper, I shall try segmenting the nerve structures in ultrasound images without using Neural Networks or any other Machine Learning Algorithms. But by simply using the platform of MATLAB (R-2016 a). Although the results of the previous works were very much satisfactory but I would like to test if this segmentation could be done without using Neural Networks and if yes, then with how much efficiency. The result is computed by comparing our output with the already given annotated ground-truths.

MATERIALS AND RESEARCH METHODOLOGY

- MATERIALS
  - DATASET

The dataset provided consists of large training set of ultrasound images, in which the nerve structure is manually annotated by trained experts. The experts make their mark on the basis of their confidence of existence of BP in the image. Given below are two images, one is the ultra sound image itself and the other is the human annotation.



(fig.9)

(a.)the input image in grayscale (b.) the desired output in binary image

The white region represents our region of interest. The model which we will build will take the gray scale ultrasound image in (a.) as input and outputs a binary mask, similar to the binary image in (b.). It has to be noted that the output is not gray scale. The intensities will be exclusively either 0 or 255.

Priori analysis of the data reveals that about 60% of the images do not possess a mask, implying that they have no BP landmark. Other notable key points about the dataset are as follows:

- Image size: 580x420 pixels
- 5635 training images
- 5508 testing images
- Noise and other artifacts present
- Repetition of the images

  - INCONSISTENCIES IN THE DATASET

1.> There are potential mistakes in the ground truth of the data.

There are images, which are very similar to each other yet have differing masks. One of the images has a mask while the other doesn't. The occurrence of such contrary images is highly likely in the test data-set provided.

2.> Repetition of images.

It seems that the images are frames of the ultrasound video feed, due to which we encounter multiple images which are actually the same frame.

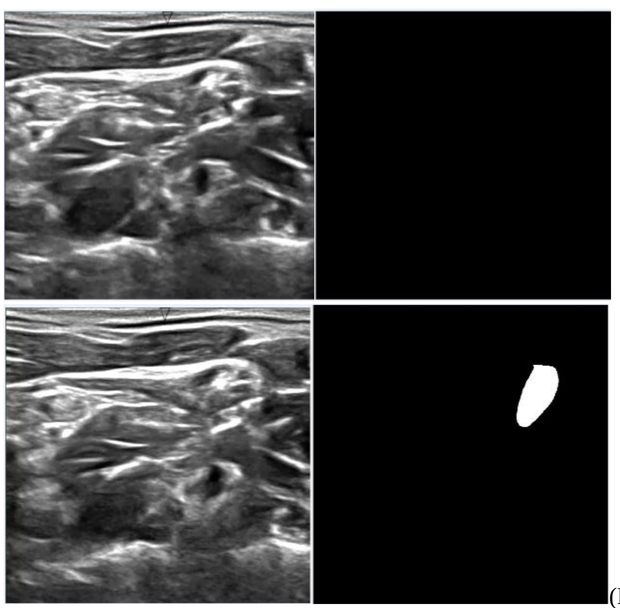
- HOW TO DEAL WITH THE INCONSISTENCIES?

1.> Removal of potentially incorrect data

In order to minimize contradictory data, we will remove all such pairs of images from data-set, which although are morphologically similar but possesses different label masks.

2.> Removal of repeated data

We will remove multiple images which are actually the same frame, keeping just one frame.



(Fig.10)

A, B, C, D from top left, top right, bottom left & bottom right. A & C are similar looking images but possesses different outputs.

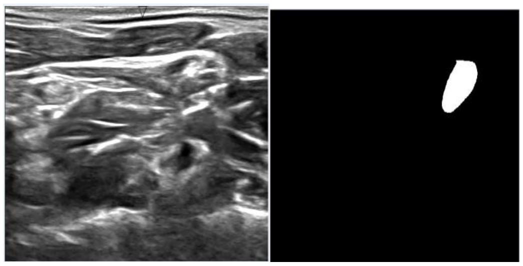
- WHICH PLATFORM HAS BEEN USED?

MATLAB (R-2016 a)

The algorithm has been designed on the platform of MATLAB.

- RESEARCH METHODOLOGY
  - IDENTIFICATION OF THE REGION OF INTEREST
    - *WHERE IS THE REGION OF INTEREST?*

      The ground-truths being provided to us were manually annotated by the experts. The region of interest was shown in the "white" color in the output of binary image.



(fig.11) (a.) the input image (b.) the ground-truth

    - *WHY WAS IT DIFFICULT TO IDENTIFY?*

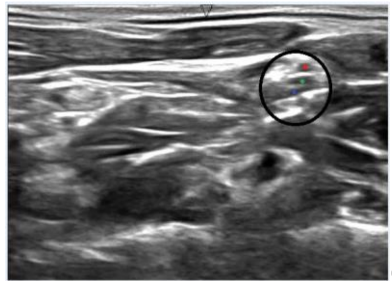
      First of all, the input image was a grayscale image and there were no visible distinguishing features, like threshold, boundary, edge and etc.

    - *HOW DID WE IDENTIFY IT?*

      We went through the structure of the nerve structure as well as the ultrasound approaches to the nerve structure to better identify the **region of interest.**

    - *WHAT DID WE FIND OUT?*

      We found out that the region of interest is actually the root of the brachial plexus and we need to locate the three trunks formed by the roots which are in the form of "three holes" in the ultrasound images. This region varies from one image to another in its shape. In some images, it is in "A" shape, in some images, it is in "R" shape, in some images it is in "S" shape and etc.


(fig.12)

the region of interest has been marked by a black circle which forms an A type shape. The red, green and blue dots respectively show the three trunks formed by the root in the form of three holes in the ultrasound image.

- READING AN INPUT IMAGE
  - *WHERE DO WE GET OUR INPUT IMAGE FROM?*

    Read an input grayscale image by browsing an image source folder named “train" which contains approximately 5000 grayscale images which are actually the ultrasound of medical images of neck-to-shoulder region either containing or not containing the brachial plexus.

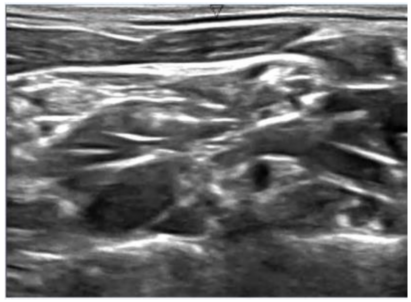
    This database was collected by the website of the KAGGLE, who had publicized this database for its own competition for the topic “SEGMENTATION OF THE BRACHIAL PLEXUS IN ULTRASOUND IMAGES". All the images are in ‘.tiff' format i.e. Tagged Image File Format.

  - *WHAT TYPE OF IMAGE IS IT?*

    It is a grayscale image.

  - *WHAT IS A GRAYSCALE IMAGE?*

    A grayscale image is one in which the value of each pixel is a single sample representing only an *amount* of light, that is, it carries only the intensity information. Grayscale images, a kind of black-and-white or gray monochrome, are composed exclusively of shades of gray. The contrast ranges from black at the weakest intensity to white at the strongest.



(fig.13) the original input Image.

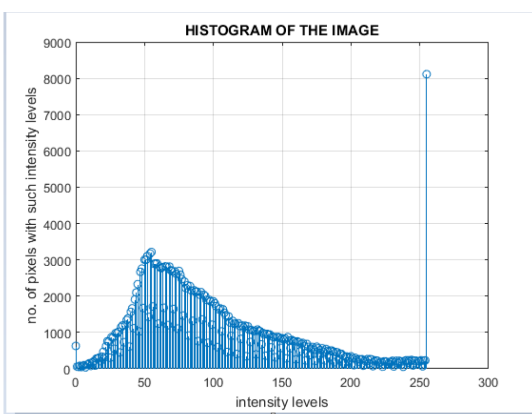
- COMPUTING A HISTOGRAM
  - *WHAT IS AN IMAGE HISTOGRAM?*

    An image histogram, shows the frequency of pixels intensity values. In an image histogram, the x axis shows the gray level intensities and the y axis shows the frequency of these intensities.

  - *WHY COMPUTE THE IMAGE HISTOGRAM?*

    1. For the analysis of the image. We can predict about an image by just looking at its histogram. It is just like looking at an x-ray of a bone of a body.
    2. For brightness purposes. The histograms have wide application in image brightness. Not only in brightness, but histograms are also used in adjusting contrast of an image.
    3. To equalize an image.
    4. Histogram has a wide use in thresholding.

  - *HISTOGRAM OF THE IMAGE*



(fig.14) Histogram of the input image

  - *WHAT DOES IT IMPLY?*

1. Image is not equalized, since the intensities aren't evenly distributed.
2. It lacks proper brightness.
3. Since it's not bimodal, it doesn't provide us with any one single threshold value.

- PRE-PROCESSING
  - *WHAT IS PRE-PROCESSING?*

    preprocessing describes any type of processing performed on raw data to prepare it for another processing procedure.

  - *WHY DO WE NEED PRE-PROCESSING?*

    Most preprocessing steps that are implemented are either to reduce the noise, to reconstruct an image, to perform morphological operations and to convert the image to binary/grayscale so that operations can be easily implemented on the image. The aim of pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing.

  - *DIFFERENT TECHNIQUES FOR PRE-PROCESSING?*

    1.> HISTOGRAM EQUALIZATION

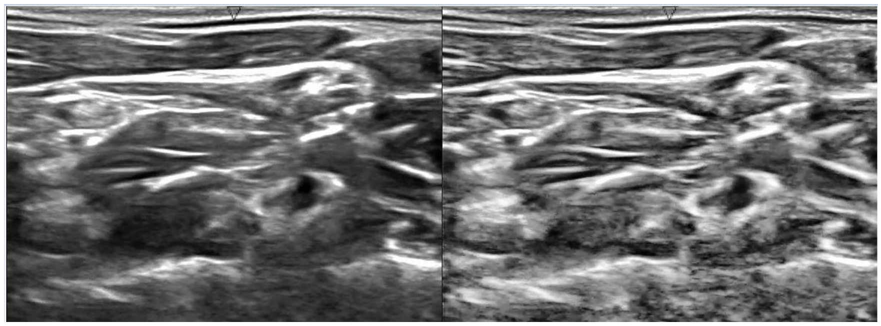
    Histogram equalization is a method in image processing of contrast adjustment using the image's histogram.

    - WHAT HAVE WE USED?

      Contrast-limited adaptive histogram equalization.

    - WHY CLAHE?

      It is used for improving the visibility of the input image. In case of CLAHE, 'distribution' parameter is used to define the shape of the histogram which produces better quality result as compared to AHE. Here, **Rayleigh Distribution** Parameters are used which creates bell shaped histogram. CLAHE can work on both grayscale and colored images.



(fig.15) (a.) the original input image (b.) after applying the CLAHE

2.> FILTERING

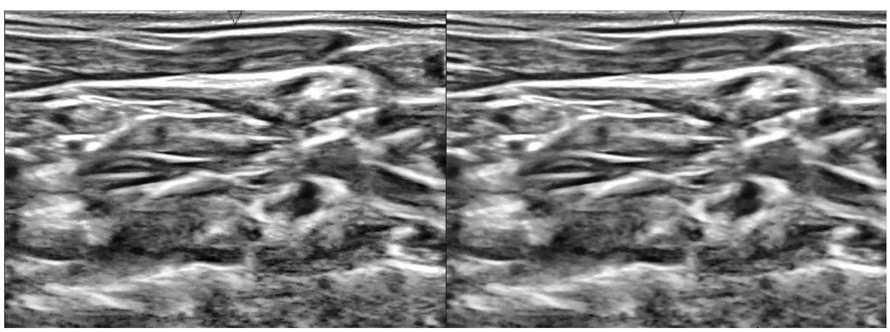
It is a pre-processing step used for removing the noise from the input image.

- WHAT HAVE WE USED?

Median filtering

- WHY MEDIAN FILTERING?

It is advantageous because it preserves edges while removing noise. Appropriate for removing speckle noise usually available in ultrasound images.



(fig.16) (a.) after CLAHE (b.) after applying median filter.

- THRESHOLDING
  - *WHAT IS THRESHOLDING?*

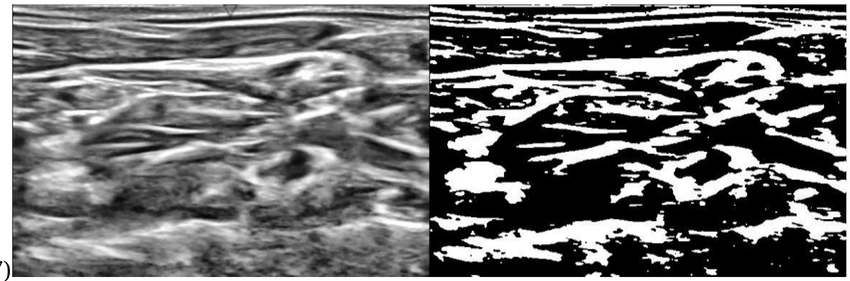
  Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images.

  - *WHY THRESHOLDING IS NEEDED?*

  Thresholding means converting an image into its binary format. It is important for image processing. Because, sometime people need a separation of dark and light region of the colorful or grayscale image.

- *WHICH THRESHOLDING ALGORITHM HAVE WE USED?*

We have used a thresholding algorithm based on the mean and standard deviation of the image.



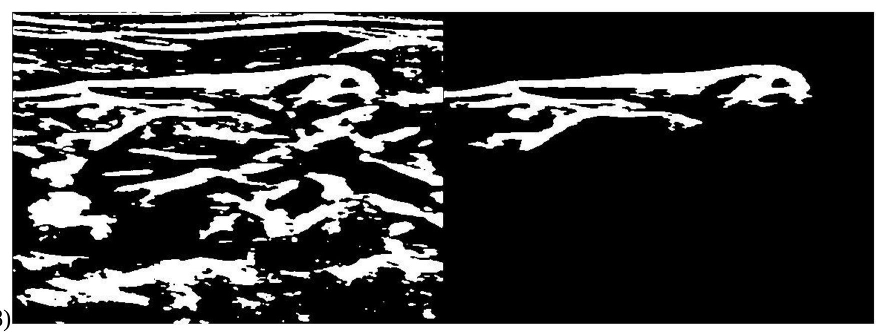
(fig.17)
(a.) after applying thresholding on (b.) (b.)

- EXTRACTION OF THE REQUIRED REGION
  - *HOW IS EXTRACTION DONE?*

We found out that the region containing the nerve structure possesses some distinguishing structural properties. These structural properties differ for images from one subset of the database to another. We extracted the required regions based on these structural properties.

- *WHAT STRUCTURAL PROPERTIES DID WE CONSIDER?*

We have considered structural properties like **Area, Euler number, Eccentricity** for extracting the desired region.



(fig.18)
(a.) (b.) after extracting the required region from (a.)

The above figure is an image from subset 1, where we have considered structural properties like “maximum area" and “at least one hole" for the extraction of the required region.

APPLYING MORPHOLOGICAL OPERATIONS

- *WHAT IS A MORPHOLOGICAL IMAGE PROCESSING?*

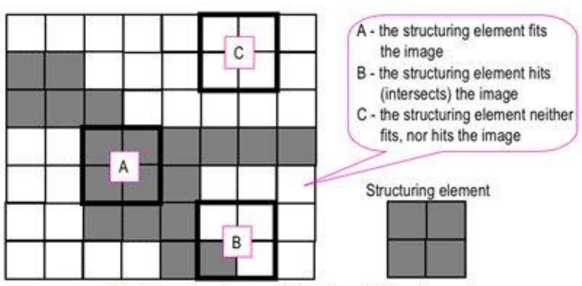
  Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image.

- *PROPERTIES OF MORPHOLOGICAL OPERATIONS*

  Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to grayscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

- *HOW DO THEY WORK?*

  Morphological techniques probe an image with a small shape or template called a **structuring element**. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "fits" within the neighbourhood, while others test whether that "hits" or intersects the neighbourhood:



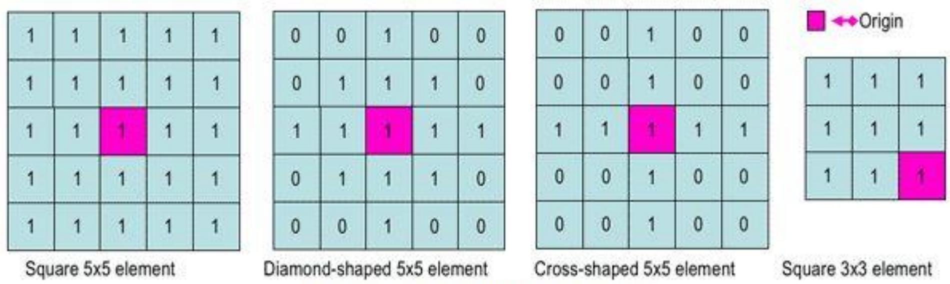
(fig.19) Probing of an image with a structuring element (white and grey pixels have zero and non-zero values, respectively).

A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image.

- *WHAT IS A STRUCTURING ELEMENT?*

  The **structuring element** is a small binary image, i.e. a small matrix of pixels, each with a value of zero or one:

- The matrix dimensions specify the *size* of the structuring element.
- The pattern of ones and zeros specifies the *shape* of the structuring element.
- An *origin* of the structuring element is usually one of its pixels, although generally the origin can be outside the structuring element.

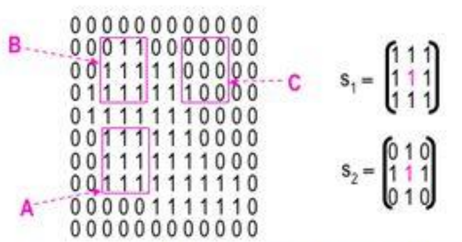


(fig.20) Examples of simple structuring elements.

A common practice is to have odd dimensions of the structuring matrix and the origin defined as the center of the matrix.

- *HOW DOES IT WORK?*

When a structuring element is placed in a binary image, each of its pixels is associated with the corresponding pixel of the neighborhood under the structuring element. The structuring element is said to **fit** the image if, for each of its pixels set to 1, the corresponding image pixel is also 1. Similarly, a structuring element is said to **hit**, or intersect, an image if, at least for one of its pixels set to 1 the corresponding image pixel is also 1.



		A	B	C
fit	s_1	yes	no	no
	s_2	yes	yes	no
hit	s_1	yes	yes	yes
	s_2	yes	yes	no

(fig.21) Fitting and hitting of a binary image with structuring elements s_1 and s_2.

Zero-valued pixels of the structuring element are ignored, i.e. indicate points where the corresponding image value is irrelevant.

- *WHAT ARE THE FUNDAMENTAL MORPHOLOGICAL OPERATIONS?*
  - EROSION

    The **erosion** of a binary image *f* by a structuring element *s* produces a new binary image $g = f \ominus s$ with ones in all locations (*x, y*) of a structuring element's origin at which that structuring element *s* fits the input image *f*, i.e. *g (x, y)* = 1 is *s* fits *f* and 0 otherwise, repeating for all pixel coordinates (*x, y*).

  - DILATION

    The **dilation** of an image *f* by a structuring element *s* produces a new binary image $g = f \oplus s$ with ones in all locations (*x, y*) of a structuring element's origin at which that structuring element *s* hits the input image *f*, i.e. *g (x, y)* = 1 if *s* hits *f* and 0 otherwise, repeating for all pixel coordinates (*x, y*). It adds a layer of pixels to both the inner and outer boundaries of regions.

- GETTING THE FINAL RESULTS

  After the required region has been extracted, we applied some of the morphological operations like erosion and dilation to extract the exact location of the region of interest.

(fig.22)
(a.) (b.) after performing morphological operations on (a.)

- THE IMPLEMENTATION OF THE PROPOSED ALGORITHM

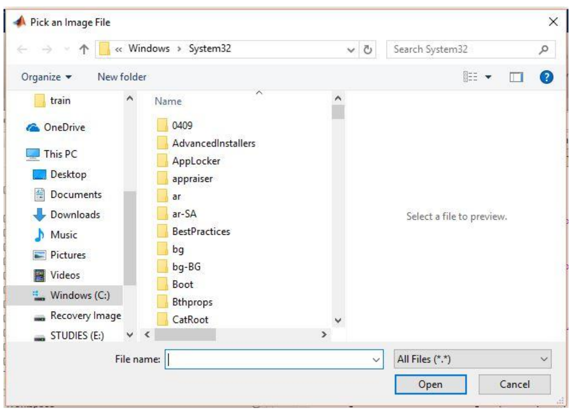
STEP 1. Delete all figures whose handles are not hidden.

STEP 2. Remove all the variables from the current workspace, releasing them from the system memory.

STEP 3. Read the input image

STEP 3.1 Provide a path to look for the folder containing the input image.

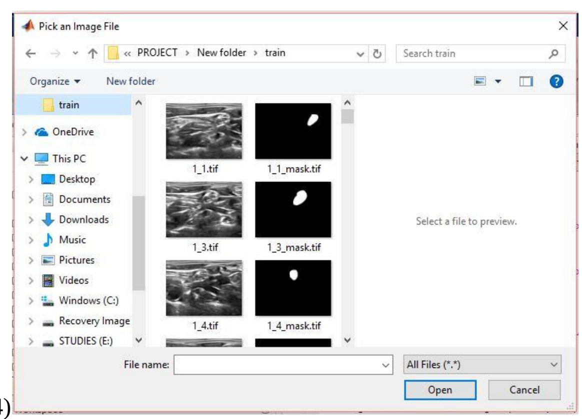
STEP 3.2 A menu window will open like this:



(fig.23)

Menu window to select the folder containing the input image

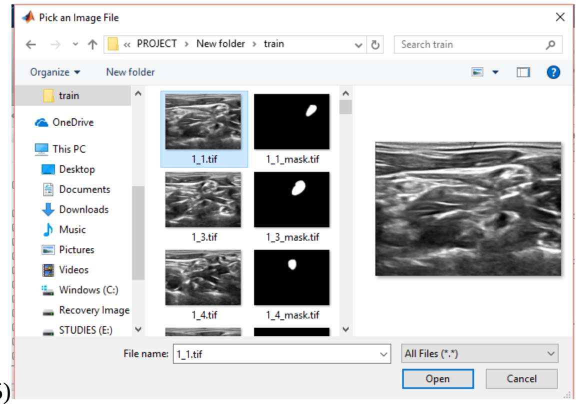
STEP 3.3 Select the folder named ‘train' on left hand side.



(fig.24)

Menu window to select ‘train' folder containing the input.

STEP 3.4 Select an image given on the right-hand side and click ‘open’.

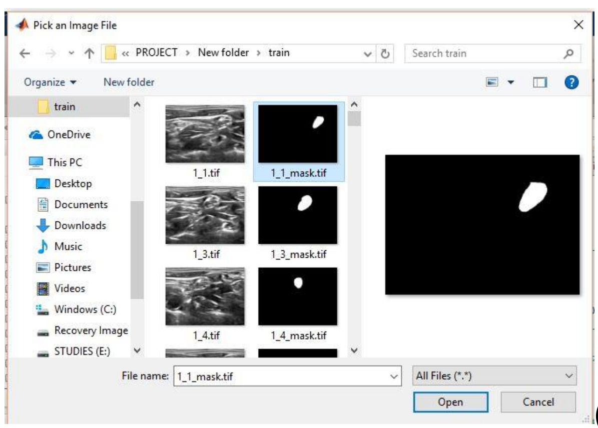


(fig.25)

Menu window to select an input image

We can select any image present in this database, one at a time, for which we want to perform the segmentation. All the images are present here with their respective 'masks' or 'ground-truths'

STEP 3.5 Repeat steps from 3.1-3.4 to select the 'ground-truth' or 'mask' of the image.



(fig.26)

Menu window to select the mask of the input image.

STEP 3.6 Store the original input image and its mask or ground-truth in two different variables.

STEP 4. Compute the histogram of the original input image.

STEP 5. Pre-processing of the original image.

STEP 6. Apply a thresholding algorithm to the original image.

STEP 7. Fill the small holes, so that while computing the Euler number, only the proper holes are being considered.

STEP 8. Extract the required region.

STEP 8.1 Label the different regions present in the original input Image.

STEP 8.2 Calculate the area of the original input image.

STEP 8.3 Calculate the ratio of ‘len/lb',where ‘len' is the length of the original image and ‘lb' is the distance between the rightmost and leftmost pixel.

STEP 8.4 Calculate the Eccentricity of the original input image, to check the ‘curviness' of the shape. If it’s a straight line, then its 1 and if circular, then its closer to 0.

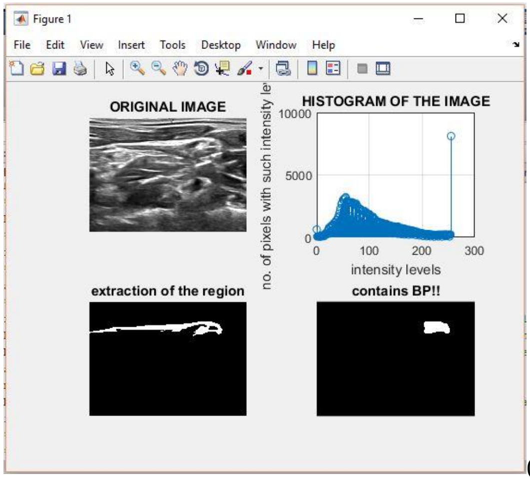
STEP 8.5 Calculate the Euler number of the original input image. The Euler Number is the total number of connected components subtracted by the total number of the holes present in the input image.

STEP 8.6 We have provided with many of the ‘classes' just for the classification of the input image, so that the further extraction of the region could be done based on that. These if conditions are designed on the basis of a certain specific range which are being provided to the above-mentioned parameters. This step is done to differentiate images from the different subsets given in the database. Although all the images are grayscale and of the same size but they vary in their shapes and hence this necessary step.

STEP 8.7 Once the classification of the input image is being done, then we further check its structural properties, which may vary for each classification, and then extract the required region.

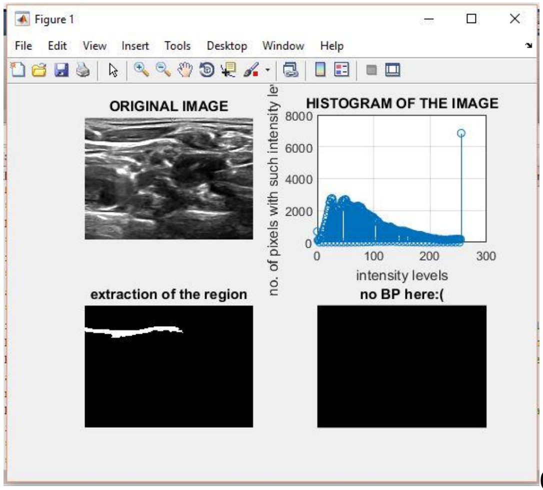
STEP 9. Apply the morphological operations to the extracted region.

STEP10.Display the output image.



(fig.27)

Display of the final output of the input image containing the BP



(fig.28)

Display of the final output of the input image not containing the BP

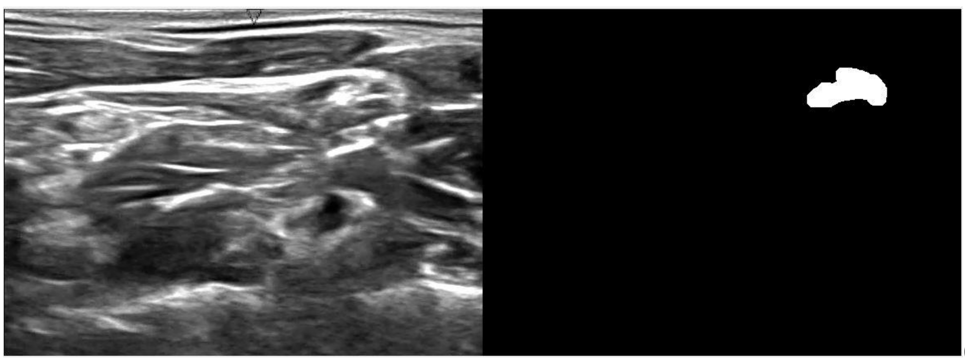
RESULTS & DISCUSSION

- ## RESULTS

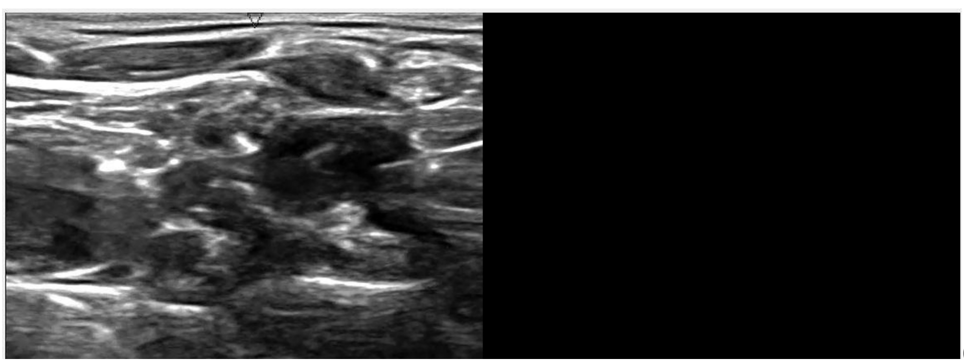
We tried to segment the nerve structure (Brachial Plexus) from the ultrasound images based on our proposed algorithm.

- ### SUCCESSFUL CASES

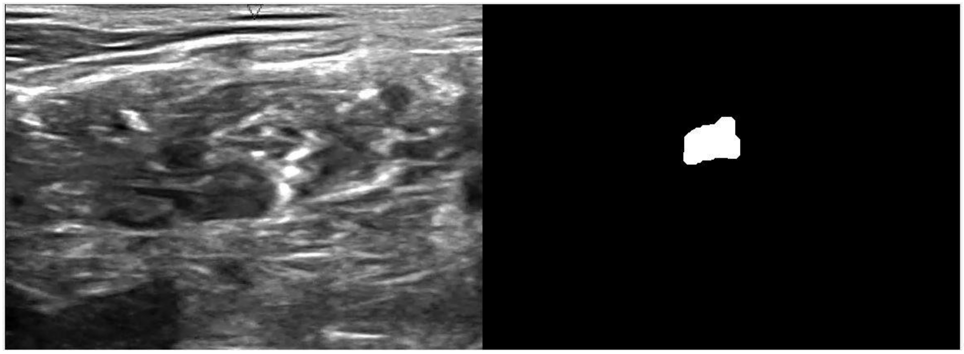
Some of the images which gave the correct output using the proposed algorithm, I. e. for images, which contained the nerve structure, its resulting output showed the presence of the nerve structure and for images, which didn't contain the nerve structure, its resulting output showed the absence of the nerve structure.

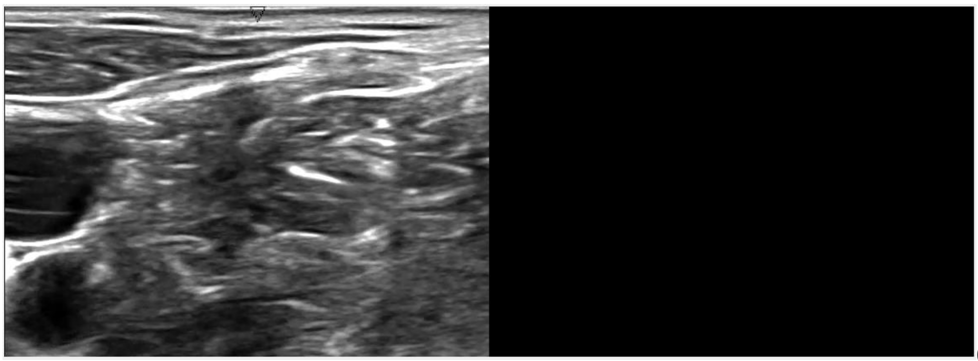


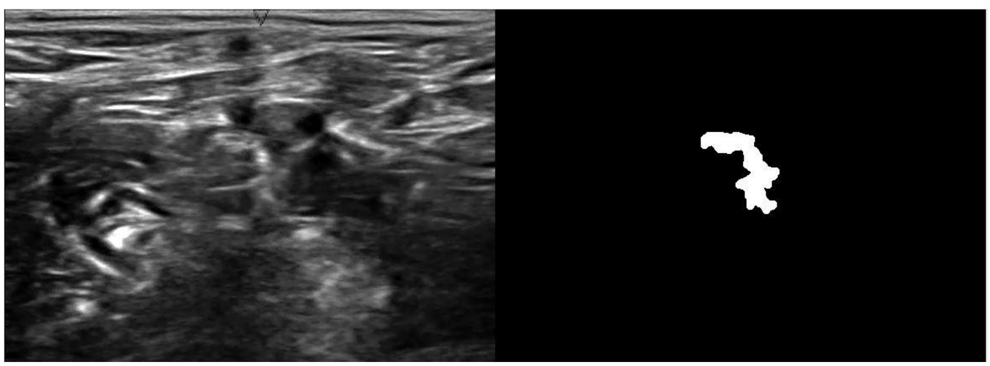
(fig.29) image from the first subset containing the BP along with its output which is giving the correct result.

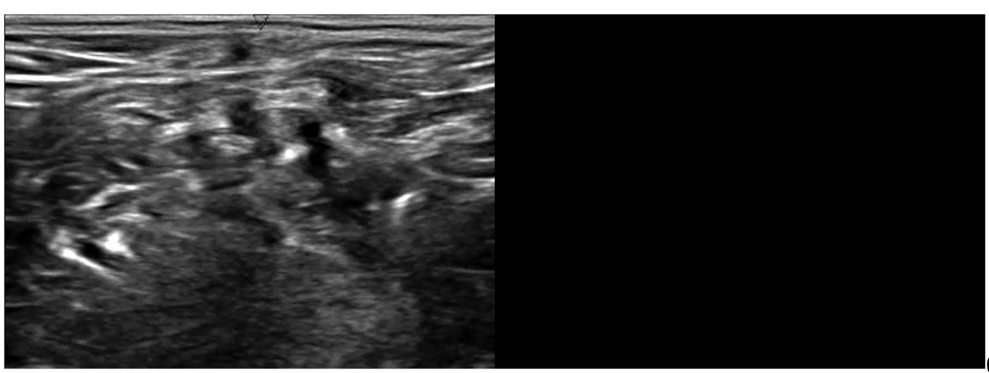


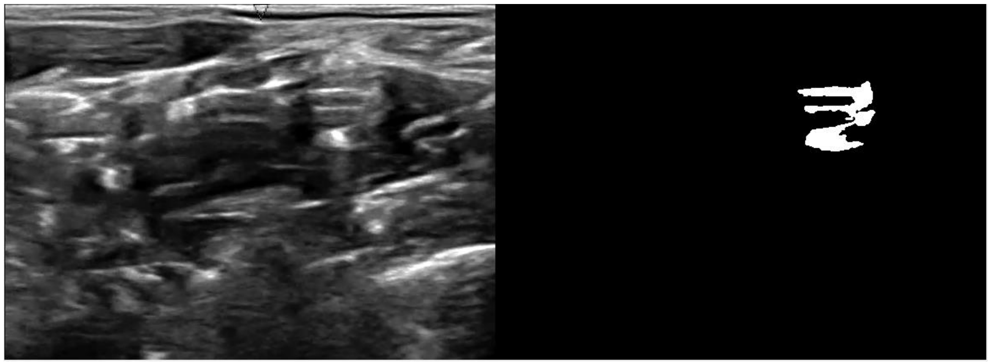
(fig30) image from the first subset not containing the BP along with its output which is giving the correct result.


(fig.31) image from the second subset containing the BP along with its output which is giving the correct result.

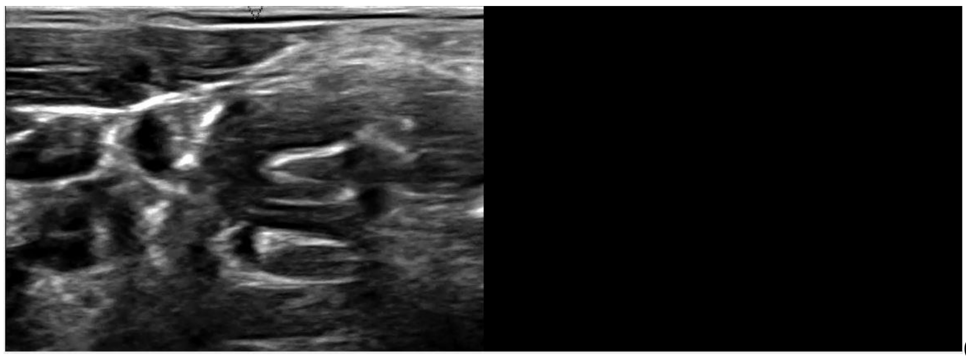

(fig.32) image from the second subset not containing the BP along with its output which is giving the correct result.


(fig.33) image from the last subset containing the BP along with its output which is giving the correct result.

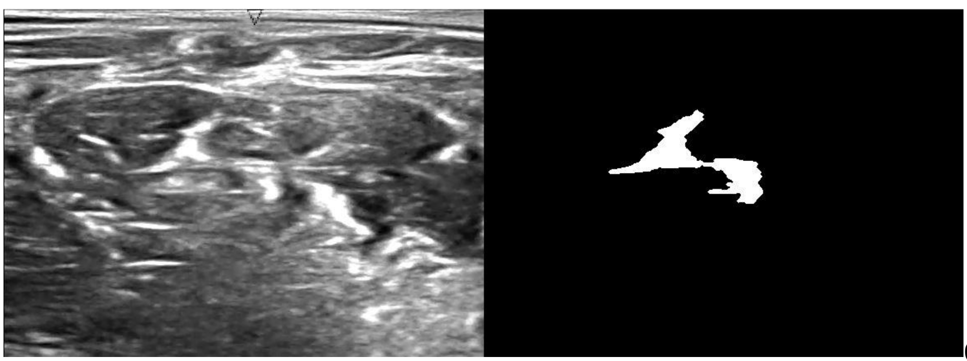

(fig.34) image from the last subset not containing the BP along with its output which is giving the correct result.



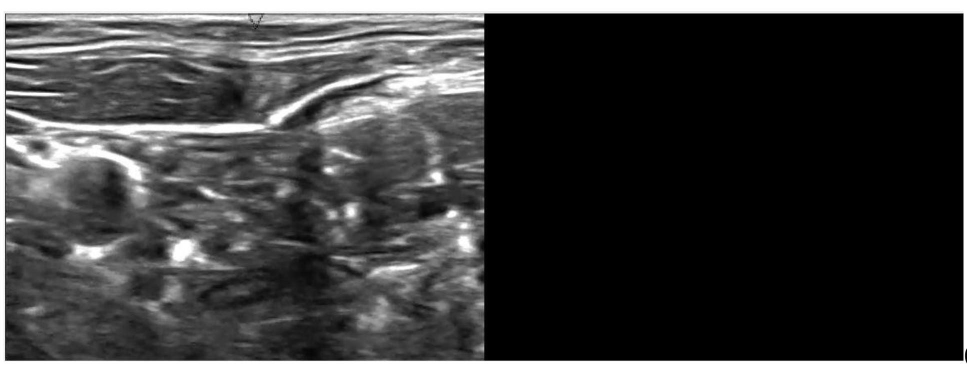
(fig.35) image from the 46th subset containing the BP along with its output which is giving the correct result.



(fig.36) image from the 46th subset not containing the BP along with its output which is giving the correct result.



(fig.37) image from the 10th subset containing the BP along with its output which is giving the correct result

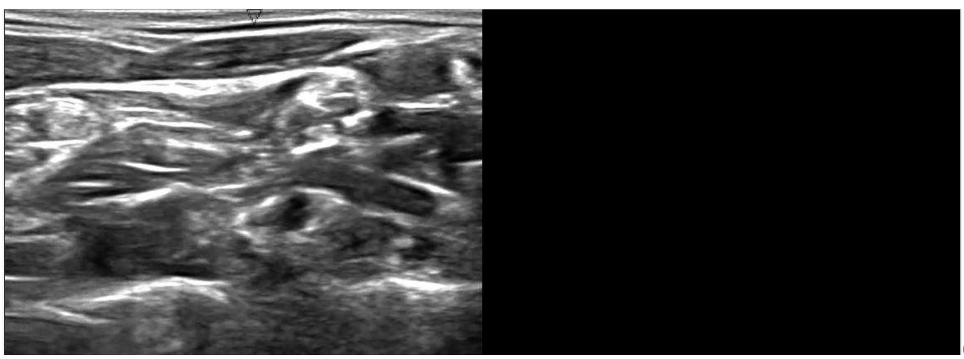


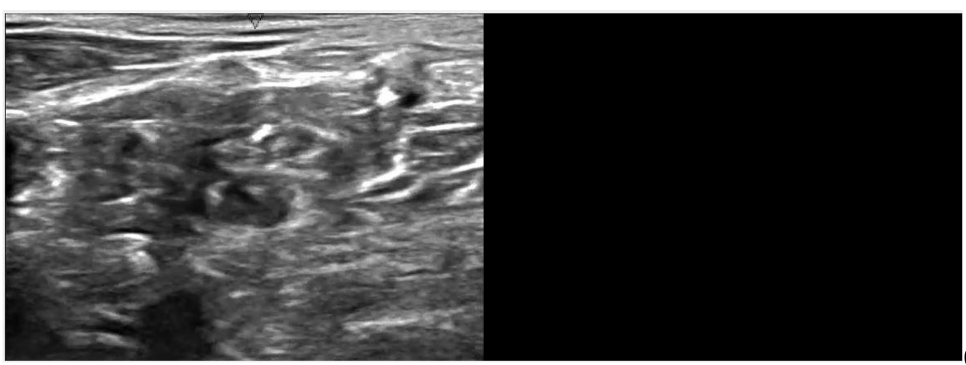
(fig.38) image from the 10th subset not containing the BP along with its output which is giving the correct result

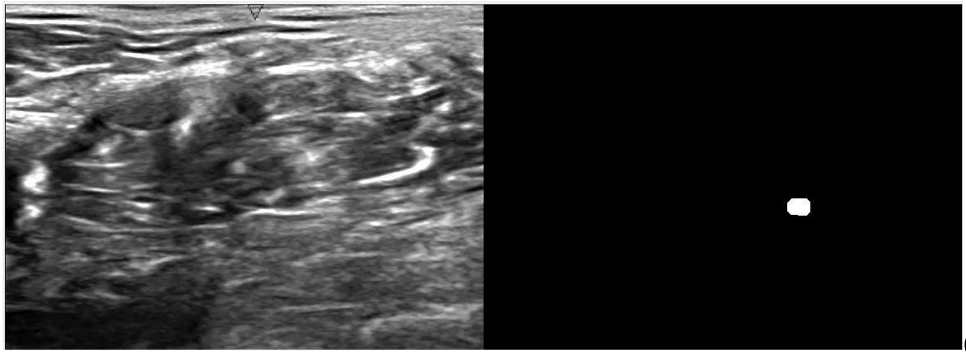
- FAILURE CASES

Some of the images gave incorrect output I. e. there were some images, which didn't contain the nerve structure but the resulting output showed its presence, and for some images, which contained the nerve structure, the resulting output didn't show its presence.


(fig.39)
image from the 1st subset not containing the BP along with its output which is giving the wrong result


(fig.40)
image from the 1st subset containing the BP along with its output which is giving the wrong result


(fig.41)
image from the 2nd subset containing the BP along with its output which is giving the wrong result

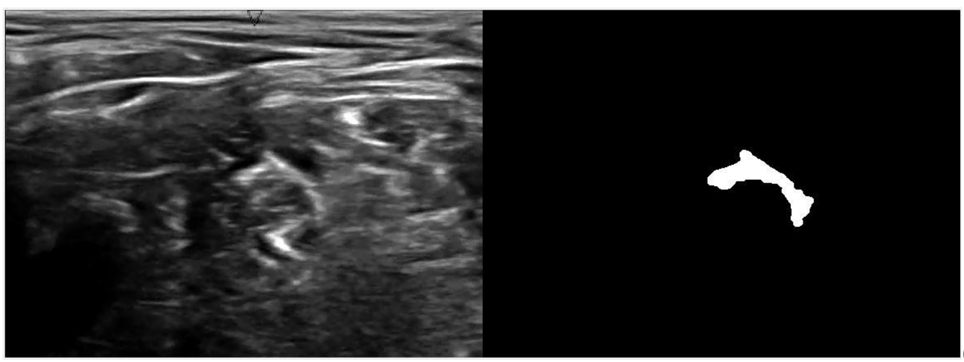


(fig.42)

image from the 2nd subset not containing the BP along with its output which is giving the wrong result

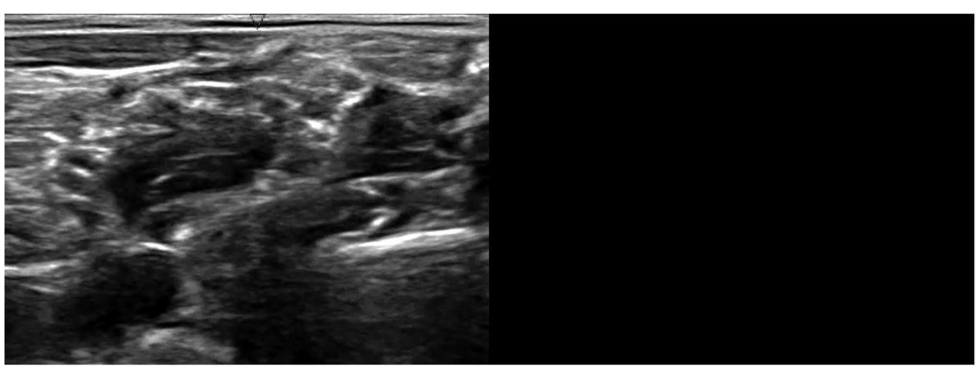
(fig.43)

image from the last subset containing the BP along with its output which is giving the wrong result



(fig.44)

image from the last subset not containing the BP along with its output which is giving the wrong result



(fig.45)

image from the 46th subset containing the BP along with its output which is giving the wrong result

○ COMPARATIVE STUDY

• RESULTS OF THE PREVIOUS WORK [ref. D. manikanta reddy]

Dice coefficient has been used as an error measure. Given two sets A and B, dice index of them is, Q=|A∩B||A|+|B|. This function penalizes any kind of wrong predictions. Just capturing the where and what is not enough, the prediction and truth have to be highly correlated. It is necessary that the binary outputs look as good as the real ones.

RESULTS

The results are computed by taking the mean of Dice score of the predicted masks with the annotated masks. The scores shown here are generated by Kaggle.

Average Dice Coefficients

Model	Best Dice Score
Blank submission[ref.d.manikanta reddy]	0.53449
Proposal Based [ref.d.manikanta reddy]	0.56527
Autoencoder [ref.d.manikanta reddy]	0.62322
U-net (without PCA) [ref.d.manikanta reddy]	0.6689
U-net (with PCA) [ref.d.manikanta reddy]	0.68719

A blank submission, itself gives us a score of 0.5 indicating that about half of the images do not contain any mask.

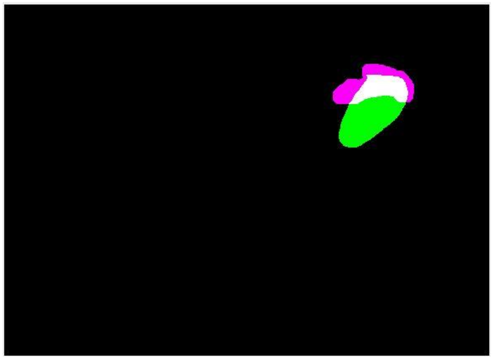
The proposal-based method used windows of size 30x30 at a stride length of 10. Experimentation with respect to window size and length is yet to be done.

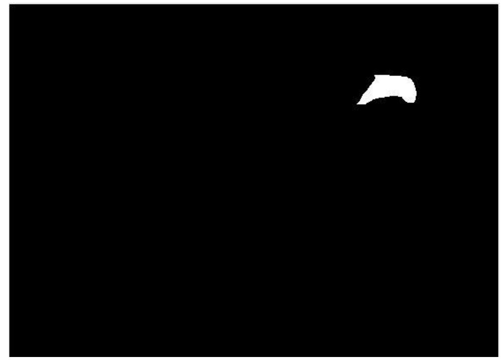
The auto-encoder based method was a huge jump from previous solutions, as it was capable enough to capture the nerve structures as we have seen.

Introducing extra connections in the encoder-decoder network to build the U-net brought the score up by 4%, indicating a strong learning of localization information.

Post processing using PCA cleaning definitely brought a final bump in the score by about 2%. A much better post processing could also work.

- COMPARISON WITH THE GROUND-TRUTH





(fig.46) (a.) shows our output in 'pink' & the ground-truth in 'green' (b.) shows the intersection region between them.

(fig.47) image shows the absolute difference between 46. (a.) & (b.)

Now, to calculate the accuracy of our extracted output, we first of all, calculate the total number of white pixels common in between our output and the ground-truth (shown in fig. 49.b) and termed as 'jk' and then we calculate the total number of white pixels in the region of absolute difference given by our output and the given ground-truth (shown in fig.50) and termed as 'acn'.

1. For Fig.29

   Countd1(I.e. sum of pixels for jk) = 1553

   aacn (I.e. sum of pixels for can) = 4633

   Ratio = 1553/4633 = 33.5

2. For fig. 31

   Countd1(I.e. sum of pixels for jk) = 204 aacn (I.e. sum of pixels for can) = 7954

Ratio = 204/7954 = 2.56

3. For fig. 33

Countd1(I.e. sum of pixels for jk) = 1856

aacn (I.e. sum of pixels for can) = 6788

Ratio = 1856/6788 = 27.3

- STATISTICAL REPORT
  - SUBSET 1st:(1_1.tif to 1_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	60
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	41
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	24
PERCENTAGE OF THE CORRECT RESULT	58%

  - SUBSET 2nd:(2_1.tif to 2_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	6
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	4
PERCENTAGE OF THE CORRECT RESULT	67%

  - SUBSET 3rd:(3_1.tif to 3_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	42
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	25
PERCENTAGE OF THE CORRECT RESULT	60%

  - SUBSET 4th:(4_100.tif to 4_109.tif)

TOTAL NUMBER OF IMAGES	10
AFTER REMOVAL OF INCONSISTENT DATA	9
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	0
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	0
PERCENTAGE OF THE CORRECT RESULT	NA

  - SUBSET 5th:(10_1.tif to 10_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	51
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	25
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	17
PERCENTAGE OF THE CORRECT RESULT	68%

  - SUBSET 6th:(11_1.tif to 11_120.tif)

TOTAL NUMBER OF IMAGES	120

AFTER REMOVAL OF INCONSISTENT DATA	87
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	63
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	30
PERCENTAGE OF THE CORRECT RESULT	48%

- SUBSET 7th:(12_1.tif to 12_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	51
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	13
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	7
PERCENTAGE OF THE CORRECT RESULT	54%

- SUBSET 8th:(13_1.tif to 13_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	81
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	60
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	17
PERCENTAGE OF THE CORRECT RESULT	74%

- SUBSET 9th:(14_1.tif to 14_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	51
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	32
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	6
PERCENTAGE OF THE CORRECT RESULT	20%

- SUBSET 10th:(15_1.tif to 15_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	51
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	25
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	17
PERCENTAGE OF THE CORRECT RESULT	74%

- SUBSET 11th:(16_1.tif to 16_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	70
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	35
PERCENTAGE OF THE CORRECT RESULT	50%

- SUBSET 12th:(17_1.tif to 17_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	16
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	4
PERCENTAGE OF THE CORRECT RESULT	25%

- SUBSET 13th:(18_1.tif to 18_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	14
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	4

PERCENTAGE OF THE CORRECT RESULT	29%

- SUBSET 14th:(19_1.tif to 19_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	63
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	14
PERCENTAGE OF THE CORRECT RESULT	22%

- SUBSET 15th:(20_1.tif to 20_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	66
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	10
PERCENTAGE OF THE CORRECT RESULT	15%

- SUBSET 16th:(21_1.tif to 21_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	23
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	14
PERCENTAGE OF THE CORRECT RESULT	60%

- SUBSET 17th:(22_1.tif to 22_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	11
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	8
PERCENTAGE OF THE CORRECT RESULT	72%

- SUBSET 18th:(23_1.tif to 23_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	120
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	92
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	
PERCENTAGE OF THE CORRECT RESULT	77%

- SUBSET 19th:(24_1.tif to 22_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	68
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	27
PERCENTAGE OF THE CORRECT RESULT	40%

- SUBSET 20th:(25_1.tif to 25_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	32
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	10
PERCENTAGE OF THE CORRECT RESULT	30%

- SUBSET 21st:(26_1.tif to 26_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	100
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	49
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	7
PERCENTAGE OF THE CORRECT RESULT	15%

- SUBSET 22nd:(27_1.tif to 27_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	4
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	3
PERCENTAGE OF THE CORRECT RESULT	75%

- SUBSET 23rd:(28_1.tif to 28_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	48
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	4
PERCENTAGE OF THE CORRECT RESULT	10%

- SUBSET 24th:(29_1.tif to 29_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	59
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	24
PERCENTAGE OF THE CORRECT RESULT	40%

- SUBSET 25th:(30_1.tif to 30_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	29
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	14
PERCENTAGE OF THE CORRECT RESULT	50%

- SUBSET 26th:(31_1.tif to 31_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	39
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	10
PERCENTAGE OF THE CORRECT RESULT	25%

- SUBSET 27th:(32_1.tif to 32_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	118
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	96
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	19
PERCENTAGE OF THE CORRECT RESULT	20%

- SUBSET 28th:(33_1.tif to 33_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	18

TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	4
PERCENTAGE OF THE CORRECT RESULT	22%

- SUBSET 29th:(34_1.tif to 34_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	112
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	76
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	20
PERCENTAGE OF THE CORRECT RESULT	26%

- SUBSET 30th:(35_1.tif to 35_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	112
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	60
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	16
PERCENTAGE OF THE CORRECT RESULT	26%

- SUBSET 31st:(36_1.tif to 36_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	48
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	28
PERCENTAGE OF THE CORRECT RESULT	60%

- SUBSET 32nd:(37_1.tif to 37_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	118
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	107
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	11
PERCENTAGE OF THE CORRECT RESULT	10%

- SUBSET 33rd:(38_1.tif to 38_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	112
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	60
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	6
PERCENTAGE OF THE CORRECT RESULT	10%

- SUBSET 34th:(39_1.tif to 39_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	117
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	0
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	0
PERCENTAGE OF THE CORRECT RESULT	NA

- SUBSET 35th:(40_1.tif to 40_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	109
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	0
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	0
PERCENTAGE OF THE CORRECT RESULT	NA

- SUBSET 36th:(41_1.tif to 42_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	66
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	14
PERCENTAGE OF THE CORRECT RESULT	21%

- SUBSET 37th:(42_1.tif to 42_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	92
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	68
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	17
PERCENTAGE OF THE CORRECT RESULT	25%

- SUBSET 38th:(43_1. tif to 43_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	82
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	38
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	24
PERCENTAGE OF THE CORRECT RESULT	63%

- SUBSET 39th:(44_1. tif to 44_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	79
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	58
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	14
PERCENTAGE OF THE CORRECT RESULT	24%

- SUBSET 40th:(45_1. tif to 45_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	108
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	10
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	3
PERCENTAGE OF THE CORRECT RESULT	30%

- SUBSET 41st:(46_1.tif to 46_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	102
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	11
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	2
PERCENTAGE OF THE CORRECT RESULT	18%

- SUBSET 42nd:(47_1. tif to 47_120.tif)

TOTAL NUMBER OF IMAGES	120
AFTER REMOVAL OF INCONSISTENT DATA	79
TOTAL NUMBER OF IMAGES CONTAINING THE NERVE STRUCTURE	29
TOTAL NUMBER OF IMAGES CONTAINING THE BP & GIVING THE CORRECT RESULT	17
PERCENTAGE OF THE CORRECT RESULT	59%

- DISCUSSION

We have discussed the result of our proposed algorithm and what are the problems faced by this result and how it differs from the ground-truths. Due to the below-mentioned reasons, our proposed algorithm results in a poor efficiency.

  - PROBLEMS WITH OUR OUTPUT
    - EXTRACTION OF THE REGION OF INTEREST

      So, we saw that the outputs of our proposed algorithm don't fully match with the given ground-truths. It is only able to extract a part of the region of interest instead of extracting the whole.

    - SHAPE OF THE REGION OF INTEREST

      The shape of our output varies from that of the shape of the ground-truth.

    - EFFICIENCY

      Not all the images give the correct output. For some images, we either get no output (or full black output) even when that image is containing the nerve structure or we get wrong output I.e. it does not extract at the correct location, but at some other location.

CONCLUSION & FUTURE SCOPE

This topic was given in a competition held by KAGGLE. Although it has been solved by using neural networks and resulted in a good efficiency. We tried to do it in our own way without using the neural networks.

Although it doesn't prove to be very much efficient but at least we came to know that it can be done without the neural network also.

The algorithm proposed by us is very simple, and easily understandable and hence can be improvised further.

We have considered 'mean' and 'standard deviation' for the threshold algorithm. Some other considerations can be done, which will extract the desired region in a better way.

Also, we have considered 'structural properties' for segmentation. There is a scope for doing some better feature extraction which will definitely result in a better efficiency.

Table of figures

REFERENCES

- PREVIOUS RESEARCH PAPERS
  - **Nerve structure segmentation from ultrasound images using random under-sampling and an SVM Classifier**

    C. Jimenez, et. Al. conf proc ICIAR 6 June 2018
  - **Segmentation of nerves on ultrasound images using a deep adversarial network.**

    CONG LIU, et. Al. conf proc IJICIC Feb 2018
  - **Segmentation of nerve structures in ultrasound images.**

    D. Manikanta Reddy KAGGLE competition, November 2016
  - **Automatic segmentation of nerve structures in ultrasound images using Graph Cuts and Gaussian processes.**

    Gil González J, et. Al. conf proc IEEE med biol soc.2015.
- OTHER PAPERS
  - **Segmentation of Medical Ultrasound Images using Active Contours**

    Oleg michailovich & Allen Tannenbaum conf proc IEEE 2007
  - **Medical ultrasound image segmentation using genetic active contour**

    Mohammad Talebii, et. Al. Conf proc JBiSE 2011.
  - **Segmentation Based on Level Set Method**

    Xin-Jiang, et. Al. Conf proc MPBE 2012
  - **Phase-based probabilistic active contour for nerve detection in ultrasound images for regional anesthesia**

    Adel Hafianea et. Al conf proc CBM 2014
  - **Nerve Segmentation in Ultrasound Images**

    Vidushi Vashishtha & Dr. Aju D conf proc I -PACT 2017
- TEXTBOOK
  - B. D. Chaurasia's Human Anatomy (volume-1)
- INTERNET WEBSITES
  - Wikipedia
  - Radiopedia
- OTHERS
  - MATLAB Documentation
  - MATLAB Help Centre