

# Ultrasound Nerve Segmentation

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**Abstract—** The medical industry has given us incredible, previously unimagined facilities today. Accurate ultrasonic nerve segmentation has drawn a lot of interest since it helps ensure the effectiveness of regional anesthesia, minimize surgical damage, and hasten the healing process after surgery. However, accurate brain ultrasound segmentation is challenging to accomplish because of the features of excessive noise and low contrast in ultrasonic pictures. One significant drawback of these noise is that it might be challenging for medical professionals to pinpoint the precise nerve in which to administer anesthesia. Using CNN and U-Net, we were able to recognize nerve structures in ultrasound pictures. Determine the image's presence or absence of the disease and its context by reducing the size of the image.

**Keywords—**Machine learning; Python; Ultrasound images; Nerve segmentation

## 1. INTRODUCTION

Ultrasound scans have very wide range of application area in the medical Field because they are cheap and easy to produce and we have many instruments available to take these scans. Ultrasound scans are mainly used to diagnose and analyze the internal body structures like muscles, nerves etc. So to accurately operate the internal body structure based on ultrasound scans is very important.

Medical imaging now includes digital image processing as a key component. We can draw attention to the key elements in any medical image that the doctors will find beneficial for research by using image segmentation. Therefore, it is crucial to precisely segment the image and supply the pertinent data, which may be easily used by doctors for a variety of medical applications. Because of their low cost, mobility, and safety, ultrasound scans are highly helpful and frequently utilized, but because of their poor image quality, we need some processing to provide us more information so that we can operate based on the ultrasound scans. Consequently, it is crucial to have a strong segmentation system for

these ultrasound scans.

Medical professionals frequently use medical imaging to view interior anatomy without opening the body. Due to a number of factors, ultrasound is one of the primary techniques utilized for imaging organs and soft tissues among the numerous medical imaging techniques including CT, PET, X-Ray, Gamma, etc. Radiation-free, non-invasive ultrasound imaging is a popular imaging method. It also offers the capability of real-time imaging. Ultrasound is a cheap method of medical imaging compared to other methods.

Over the past ten years, new methods for pre-processing, segmenting, and compressing medical images have been studied and tested in an effort to solve the aforementioned difficulties. Speckle noise is frequently seen in medical which will only temporarily numb the pain.

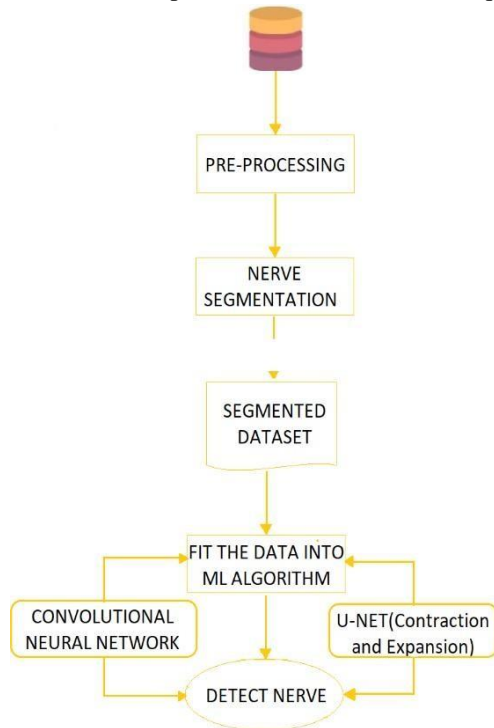
ultrasound imaging, which negatively impacts both the quality of the image and the diagnosing process. As a result, it's crucial to eliminate speckle noise from the image during pre-processing.

In this review paper we are trying to tensor filters which have been used in pre-processing the image and image segmentation techniques and image compression techniques is discussed in section III, in section IV, introduction to Region of Interest is given.

## 2. LITERATURE SURVEY

The first approach that Hui Wang, Ting-Zhu Huang, and Yugang Wang proposed in 2016. They employed the active contours method in this paper. This technique divides image segmentation in ultrasound pictures into two steps. In an ultrasound image, they applied global segmentation in the first stage and local segmentation in the second stage. They claim to have used a window function to achieve local segmentation and a Gaussian Distribution for global segmentation. The second stage makes additional use of the information obtained in the first stage of local segmentation. Results from the second step therefore depend on the accuracy of the first stage's results. If

the first stage's results are accurate then the second stage's results will be more precise. Demonstrates how a comparison of various techniques for



extracting features from an ultrasound image is made. And after comparing several approaches, the Hough transform is employed to build the model. In this article, the author discusses a technique for quickly administering anesthetic to a blocked location in order to locate the blocked area or region of interest on an ultrasound image.

The next paper proposed, which Deep Gupta and R.S. Anand proposed in 2016–17, employed a hybrid method for ultrasonic picture segmentation. In this hybrid approach, they have used edge-based active contour method with the usage of distance regularized level set function and kernel fuzzy clustering with spatial constraints. In order to detect object boundaries, the kernel fuzzy clustering findings are helpful. Because nothing in the level set function needs to be reinitialized, the processing performance of this distance regularized level set function is likewise quite high.

The following techniques are employed:

Clustering using kernel fuzzy C-means: It operates under the premise that related data should be gathered into one cluster. By reducing the cost function, related pixels or data points are grouped in this way. The Euclidian distance of the pixels from

the centroids of the other clusters is the foundation of this cost function. Model for level set segmentation with distance regularization: This is used to address the issue of dynamic variation boundaries in ultrasound images.

The following is a description of each stage in detail: Distance regularization has been used in this potential function. This method is utilized using ultrasound pictures' contour forms. Hybrid Approach: To segment the edges in the ultrasound pictures, they combined edge-based active contour approach with fuzzy C methods.

### 3. PROPOSED METHODOLOGY

In this proposed method we have divided this image processing into three different parts. The architecture for the same has shown below:

1. Image pre-processing.
  2. Nerve Segmentation.
  3. Machine learning.
- CNN Algorithm
  - U-Net Algorithm:

Following the use of the segmentation algorithm for edgedetection in the images, we will first filter the image data set that we obtained from any source, such as a database, in the diagram above. Then, in order to train the system, we will fit this split data into a machine learning algorithm.

Image pre-processing:

In this module, we pre-processed the ultrasound images using a few different methods. It is challenging to extract information from ultrasound images since they have speckle noise in them. Therefore, to reduce the speckle noise in ultrasound images, we have applied several filters such as tensor filter to the images.

Nerve Segmentation:

Following the application of image pre-processing, we obtain pre-processed images free of all noise. These pictures could also be employed for image segmentation. We have utilized the highly effective CNN algorithm or U-Net technique in Python for image segmentation in order to separate the nerve area from ultrasound pictures. 2D arrays are created from

the input images. We provided input for the train and test images in this, and the images were then transformed into arrays and saved as arrays. We were able to accomplish this with the aid of a Python numpy array. We will now feed this data into the machine learning algorithm so that it can train the system.

**Machine learning:**

Using the findings of the nerve segmentation, we will train the system in this module. The machine learning system will be fed all the data that we obtain from the nerve segmentation. To train the system for nerve segmentation in ultrasound images, we will employ convolutional neural networks and the U-Net technique. Following this training, the system will be able to identify the nerve area in a fresh set of ultrasound images.

**CNN Algorithm:**

As we see convolutional neural network is Good for image recognition in the biomedical field. In huge amount of dataset, it provides better performance than the svm and also in pixel based concept convolutional neural network is much better than svm. It has highest accuracy among all the algorithm. With Little dependence. A common artificial neural network used for object and image recognition and classification is the convolutional neural network, or CNN. Thus, Deep Learning uses a CNN to identify items in an image. A grayscale image is the same as an RGB image but only has one plane, whereas an RGB image is nothing more than a matrix of pixel values. For more information, consider this image. Convolutional Neural Network will be used for image segmentation and classification(CNN). The output of CNN must be up-sampled in order to create a probability mask.

**U-Net Algorithm:**

U-Net, evolved from the traditional convolutional neural network. As a general convolutional neural network focuses its task on image classification, where input is an image and output is one label, but in biomedical cases, it requires us not only to distinguish whether there is a disease, but also to localize the area of abnormality. U-Net is dedicated to solving this problem. The reason it is able to localize and distinguish borders is by doing classification on every pixel, so the input and output

share the same size.

First sight, it has a “U” shape. The architecture is symmetric and consists of two major parts — the left part is called contracting path and the right part is expansive path.

**Contraction Path:**

It finds the context of the image-size and shape suppose pixels It is constituted by the general convolutional process.

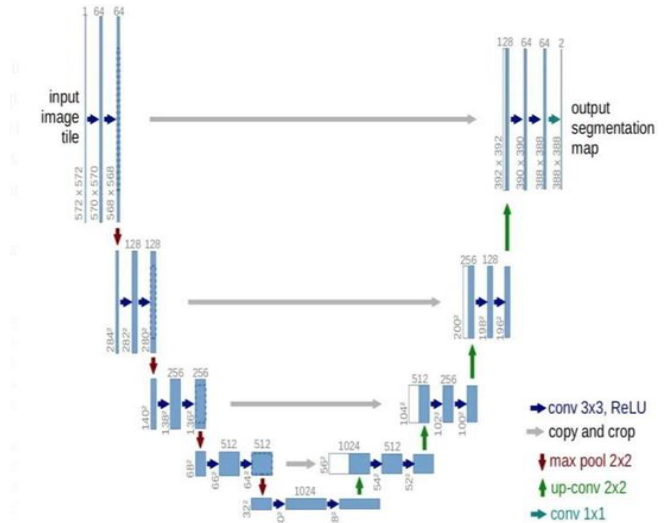
The contracting path follows the formula:

conv\_layer1 -> conv\_layer2 -> max\_pooling -> dropout(optional)

**Expansion Path:**

In the expansive path, the image is going to be upsized to its original size.

The formula follows:

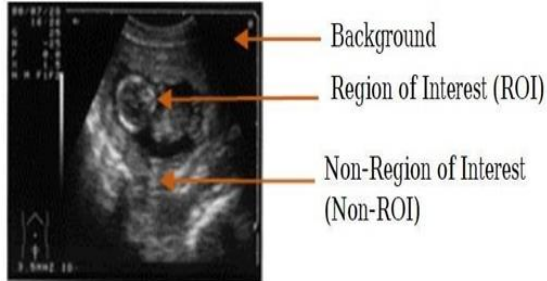


conv\_2d\_transpose -> concatenate -> conv\_layer1 -> conv\_layer2

**4.REGION OF INTEREST**

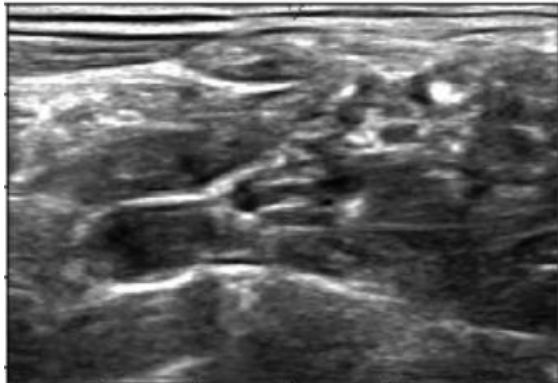
A medical image's various components do not all contribute equally to the clinical diagnosis, but in the majority of cases, a very small portion of the image is sufficient. Accordingly, the three components of a medical image are the region of interest (ROI), region of interest (ROI), background, Non-ROI, and the image itself. Image segmentation is the process of removing Region of Interest from a medical image. Additionally, it's crucial to perform an effective image compression.

The smallest area in a medical imaging is the region of interest. However, it is the most significant and crucial area because it contains the most important data in the medical imaging. A current active study field is the determination of ROI using manual, automatic, or semi-automatic procedures.

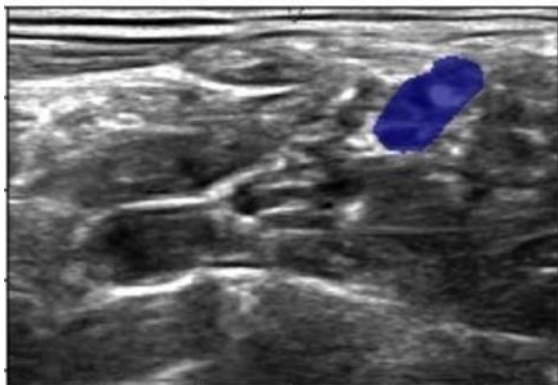


### 5.RESULT

The image data set utilized in this study for segmentation and machine learning is shown below:  
Original Image:



Segmented Image :



### 6.CONCLUSION AND FUTURE WORKS

With the aid of many modules, the nerve area in the

ultrasound image has been created. so that medical professionals may quickly identify the nerve location where they need to provide a medication. Many people can benefit from using this application to shield themselves from the negative effects of the anesthetic that has been put into their bodies during the operation of various body parts. Due to the accessibility and affordability of ultrasound scans, this application will have a significant impact on the medical industry.

Additionally, because of machine learning, clinicians won't need to worry about the treatment because the system will train itself through learning and provide results that are superior to those produced by humans. Because surgeons won't have to exert any effort to locate any nerves in ultrasound scans, any surgery will be fairly simple.

This review paper examines the techniques for pre-processing, segmenting, and compressing ultrasonic images. In order to improve patient management, our analysis will be helpful in implementing improved pre-processing, segmentation, and compression in medical ultrasound images.

- 1) Trans-UNet: Transformers Make Strong Encoders for Medical Image Segmentation:
- 2) Deployment of the model in a mobile device using Tensor Flow lite.

### REFERENCES

- [1] Mayer, M. A., et al. "Automatic nerve fiber layer segmentation and geometry correction on spectral domain OCT images using fuzzy C-means clustering." *Investigative Ophthalmology & Visual Science* 49.13 (2008): 1880-1880.
- [2] Potočnik, Božidar, and Damjan Zazula. "Automated analysis of a sequence of ovarian ultrasound images. PartI: segmentation of single 2D images." *Image and Vision Computing* 20.3 (2002): 217-225
- [3] Huang, Qinghua, et al. "Optimized graph-based segmentation for ultrasound images." *Neurocomputing* 129(2014): 216-224
- [4] Kaur, D. and Kaur, Y. (2014) "Various Image Segmentation Techniques: A Review", *International Journal of Computer Science and Mobile Computing*, 3(5), pp. 809-814.
- [5] Yogamangalam, R. and Karthikeyan, B. 2013 "Segmentation Techniques Comparison in Image

Processing”, International Journal of Engineering and Technology (IJET). 5(1), pp. 307-313

[6] An, Jung-Ha, Paul Bigeleisen, and Steven Damelin. "Identification of Nerves in Ultrasound Scans Using a Modified Mumford-Shah Functional and Prior Information." Proceedings of the World Congress on Engineering and Computer Science. Vol. 1. 2011.

[7] Hetz, Walter, and Peter Weber. "Manually operated ultrasound application." U.S. Patent No. 4,545,386. 8 Oct. 1985

[8] Chitchian, Shahab, et al. "Combined image-processing algorithms for improved optical coherence tomography of prostate nerves." Journal of biomedical optics 15.4 (2010):046014-046014.

[9] Noble, J.A., "Reflections on ultrasound image analysis", Medical Image Analysis (2016), 33, pp. 33–37.

[10] Garcia, Julian PS, et al. "Optic nerve measurements by 3Dultrasound-based coronal" C-scan" imaging." Ophthalmic Surgery, Lasers and Imaging Retina36.2 (2005): 142-146.