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A Literature Review on Segmentation of Medical Images using U-Net and Other Techniques

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Abstract - Image segmentation's digital image processing subfield has numerous applications in image analysis. The growing science of medical image analysis has made it difficult to segment regions, disorders, or anomalies in medical imaging. Monitoring the growth of conditions like plaque and tumors is made easier with the help of medical image segmentation. Areas of interest (ROIs) from the dataset are extracted as a component of medical image segmentation. such as that from ultrasound imaging (US). Medical image segmentation can take a long time, but recent advancements in software techniques like Deep Learning, Machine Learning, and Artificial Intelligence (AI) are making routine tasks easier to complete. so that it makes it possible to analyze anatomical data with greater precision by separating out only the essential regions. The segmentation of intima carotids and media on an ultrasound image is crucial for reducing the annual number of deaths caused by atherosclerosis. Plaque, or the accumulation of fats, cholesterol, and other substances on and within the artery walls, is known as atherosclerosis. Recently, a number of image segmentation tasks have implemented deep neural network models. In this survey, we look at the previous research that a number of authors have done on segmentation using a variety of methods, such as the U-net (U-Net architecture was developed with minimal changes to CNN architecture) and its variants. For better understanding, we have also studied a few more techniques of Segmentation in addition to U-net.

***Key Words*:** Intima media, Atherosclerosis, U-Net, Segmentation, carotid artery, ultrasound imaging.

1. INTRODUCTION

Image segmentation's primary goal is to transform an image's representation into something more insightful and understandable. The poor image quality makes automated segmentation of carotid artery ultrasound images quite difficult. Atherosclerosis is the accumulation of fats, cholesterol, and other substances in and on the artery walls, which leads to the buildup of plaques in the artery's inner lining that results in the arteries being thicker or harder. As a result, Carotid intima-media can be seen by medical professionals to identify pathogenic modifications in the patient's carotid artery internal structure. neural networks using convolutions (CNN) with a U-Net or other construction with a U form demonstrated Deep neural networks have lately been employed for automated segmentation, and biomedical image segmentations have shown encouraging results. [3]. U-net is a method for image segmentation that was developed primarily for use in image segmentation tasks. As a result, it has become widely used in medical imaging as the primary tool for segmentation tasks.

The U-Net architecture, which was first published in 2015, sparked a deep learning revolution. At the International Symposium on Biomedical Imaging 2015 (ISBI) cell tracking challenge, the design easily outperformed the competition in a number of areas. Segmenting neural structures in transmitted light microscopy pictures and electron microscopy stacks are a few of their accomplishments. The U-Net is an amazing design that handles the vast majority of issues. The concept of fully convolutional networks is used in this strategy. The U-Net is designed to keep track of both the characteristics of the context and the localization. The kind of architecture that was constructed effectively completes this procedure. Utilizing up-sampling operators immediately after consecutive contracting layers in order to create outputs with better resolution on the input images is the basic idea behind the implementation. Even if U-Net represents a big breakthrough in Understanding the older methods that were employed is just as crucial for deep learning to handle tasks of this nature. Therefore, in order to better understand, we have also studied a few more articles in addition to U-net.

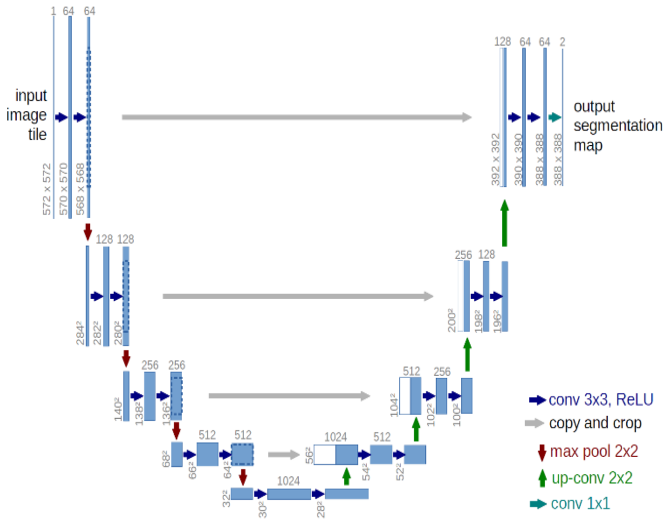

Fig: U-Net Architecture

[1] A contracting path and an expanded way make up the U-Net design. Max-pooling (Max Pool) layer with two convolutions (Conv) and two layers with kernel widths of 3 × 3 and 2 × 2 are repeatedly used in the contracting route (left path in Fig. 1). The expansive path i.e., right path in the above Figure 1 is made up of one up-sampling (up-Conv) layer, two convolution layers, and the repeat of the characteristics from similar layers in the contracting path are combined. The convolution layer's kernel is the same as the contracting paths, and the up-sampling layer's kernel is 2 × 2. There is only one 1 × 1 convolution kernel in the final layer. Except for the final layer, whose activation functions are set to SoftMax, all convolution layer rectified linear units are chosen as the activation function (ReLU).

2. Literature Survey

B. Behboodi et. al. in [1] proposed testing with phantom data from a tissue-imitating ultrasound machine, the U-Net deep learning segmentation architecture using simulated ultrasound (US) images. As a result, according to their research, simulated data can be used in place of datasets that are unavailable or don't have enough training data. Using the U-Net architecture, they learned the segmentation masks from the simulated US photos. The trained network is then used to predict the segmentation masks of the tissue-imitating phantom data. They used two metrics, F2 and Coefficient of Dice Similarity (DSC), to evaluate the effectiveness of the network.

M. Amiri et. al. in [2] paper looked into the segmenting ultrasound images by fine-tuning different layer sets in a pre-trained U-Net. On the basis of two distinct shallow and deep layer definitions, two distinct schemes were examined. They specifically demonstrated that the most ineffective strategy for classification networks is frequently fine-tuning the network's final layers. When using a U-Net to segment ultrasound images, instead of adjusting the deep layers, it might be better to do so for the shallow layers. The lower-level features that shallow layers learn significantly contribute to the automatic segmentation of medical images. Additionally, they discovered that, even in the presence of a sizable Ultrasound dataset, shallow layer tuning is quicker than network tuning.

N. Siddique et. al. in [3] In this study, they want to offer a starting point for researchers interested in investigating U-net, an effective deep-learning segmentation model that is frequently used in medical imaging. They looked at the many U-net configurations and their varied uses using a wide range of imaging modalities.

Amiri et. al. in [4] used Images of the breast with malignant or benign tumors from a breast ultrasound imaging dataset. The lesions were initially located using a U-Net, and the area they located was then divided using another U-Net. They saw an overall improvement of 1.8% Using the proposed two-stage technique, the average Dice score will be increased. The improvement was significantly greater for images whose initial Dice score was less than 70%, with an improvement of 14.5% on average. As can be seen, they were confident that the results could be trusted in at least 77% of the images. However, neither the Dice score nor the segmentation accuracy was particularly high in any of these lesions that were found.

J. Ding et. al. in [5] suggested modifying the U-Net model) in this paper and it is called as ReAgU-Net, introducing Feature maps from shallow and deep layers multiplied using an attention gate mechanism. and incorporating better residual units were incorporated into the skip link between the encoding and decoding routes. The Cross-Entropy Loss, the Focal-Tversky Loss, and the Dice Loss are combined into a single hyperparameter in order to jointly manage the model optimization process. The results of the experiments show that the proposed method performs better than the other U-shaped models.

M. Xie et al. in [6] This study managed to segment plaques with an accuracy of 66.8% using a simple convolutional U-Net. They achieve an increase to 68.8% accuracy with their dual-decoder model, but only 65.1% accuracy with their two-stage approach. But when they input the genuine right vessel into the two-stage model, the Plaque precision increases to 81.7%, indicating that the system has promise but still needs improvement. The U-Net and dual decoder U-Net variants are combined, and they were able to produce segmentation confidence ratings. The U-Net dual decoder's precision increased to respective values of 75.2% and 87.3%. when high confidence outputs are taken into account over the 60% and 80% thresholds.

Meshram NH et al.in [7] This research describes the use of deep learning to segment carotid plaques in longitudinal B-mode ultrasound images. It is compared to a regular U-Net and a dilated U-Net design where the bottleneck was the dilated convolution layers. A bounding box was used in both a completely automated and a semi-automatic technique. The networks that performed significantly better when the bounding box was used were those having 0.48 U-Net Dice coefficients for automated segmentation of plaque and 0.83 for segmentation that is semi-automatic.

J. Li et al. in [8] introduced the MF U-Net stands for Fusion Multi-scale U-Net deep learning architecture, which takes the image's edge features and texture characteristics and extracts them. There are two new focal losses and modules in them. Three techniques are proposed to address the segmentation issues brought on by significant variations in breast lesions: 1) the Multi-Scale Dilated Convolutions Module, which segments amorphous and fuzzy breast lesions, and 2) the Fusion Module (WFM) (MDCM), and 3) focal-DSC loss that addresses the problems with breast lesions segmentation caused by class imbalance.

M. Xie et al [9] Here, they evaluated a U-net convolutional neural network for segmenting carotid system lumens from ultrasound images. In each image, the vessel lumen was manually split and utilized as a source of reference. They were able to achieve an accuracy of 94.3% for cross-validation with a convolutional U-Net that was 10-fold more accurate. It is clear that even the lumen is accurately segmented by the U-Net when there is substantial plaque, Ultrasound shadowing, a calcified wall, and other factors all contribute to the challenge to outline the vessel. It can likewise be seen that the normal carotid supply route vessels are simplest to fragment with a 96.6% cross-approval precision through inner and outside

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carotid are more enthusiastically both with 92.7% and 91.9% cross-approval exactness separately.

Y. Li et. al. in [10] the paper's objective is to give readers a tool for automatically segmenting lesions to help them analyze ultrasound images. They demonstrated that U-net surpasses other cutting-edge networks, achieving a Dice coefficient of 0.929, with careful hyperparameter adjustment. Following that, they suggested incorporating group convolution into U-net design. This results in the creation of the lightweight Lighter U-net @128 network, which accomplishes similar segmentation. The automated lesion segmentation is initially completed by comparing traditional networks like FCN, DeepLab v3+, and U-net.

W. Yu et al. in [11] created a new architect for the 3D Residual U-Net to separate the portal and hepatic veins from the abdominal CT volumes. They increased discriminative feature representation and increased convergence speed by incorporating the ResNet's 3D U-Net with residual block structure. A weighted Dice loss function was developed in order to address the issues of pixel imbalance, vessel boundary segmentation, and tiny vessel segmentation. Based on the predictions, the surfaces of the vessels are smoothed and noise blocks are eliminated Using methods for post-processing like 3D morphological closed operation and volume analysis.

M. Jiang et al. in [12] suggested in this study, 3D carotid ultrasonography data was used to train to segment the common carotid artery, using a convolutional neural network (CNN) (CCA). To segment, three U-Nets were employed, the ultrasound images in 3D, for the proposed CNN, these orientations are divided into axial, lateral, and frontal. They developed a brand-new SAN expanded as a segmentation average network in this research to combine the segmentation maps obtained from three U-Nets. The development of a fully automated vessel wall segmentation approach was the aim of their work.

Z. Zhou et al. [13] For semantic and instance segmentation, a revolutionary neural network called UNet++ was suggested to get beyond the drawbacks. Utilizing six distinct medical image segmentation datasets, including those from magnetic resonance imaging (MRI), electron microscopy, and computed tomography (CT), we assessed UNet++ (EM). According to their research, UNet++ performs better than U-Net and broad U-Net by an average of 3.9 and 3.4 points, respectively, than U-Net and U-Net with deep supervision.

H. Li et al. in [14] In this study, scientists looked at a new composite network called CR-UNet for segmenting ovaries and follicles on transvaginal ultrasound concurrently (TVUS). A basic U-Net is combined with a spatial recurrent neural network (RNN) adopting new architecture called CR-UNet. To handle the limitations of this job, including low picture quality, low contrast, fuzzy borders, and complicated anatomical forms, the model can successfully learn multi-scale long-range spatial contexts. They also used thorough monitoring techniques to enhance model training's efficacy and efficiency.

Y. Weng et al. in [15] The efficiency of image classification has significantly enhanced with neural architecture search (NAS). segmenting medical imaging data was added to the Neural Architecture Search in this paper. On a U-shaped backbone network, they proposed NAS-UNet, which combines a U-shaped backbone network with the same number of DownSC and UpSC. During the search phase, a differential architecture strategy simultaneously updated the DownSC and UpSC architectures. They showed that the suggested method provided successful segmentation results on the Promise12, Chaos, and ultrasonic nerve datasets, which were gathered by magnetic resonance imaging, computed tomography, and ultrasound, respectively., they demonstrated that the proposed method produced successful segmentation results.

Cao et al.in [16] In this experiment, developed a brand-new, entirely transformer-based encoder/decoder with a U shape for the segmentation of medical images. For feature representation and long-range semantic information, the Swin Transformer block is the fundamental unit of interactive learning in order to leverage the power of the Transformer. The suggested Swin-Unet has high performance and generalizability, as shown by extensive trials on cardiac and many organ segmentation tasks.

Ronneberger et al.in [17] proposed a network and training technique that makes substantial augmentation of data to make better use of the annotated examples that are already provided. The design consists of a contracting path to collect context and an expanding path that is symmetrical and allows for precise localization. They demonstrated that a network of this type can be trained end-to-end using a relatively small number of pictures and outperforms the previous best solution on the ISBI challenge for segmenting neuronal structures in electron microscopic stacks.

Wang et al.in [18] A novel EAR-U-Net network are presented in this study for automatically segmenting the liver in CT scans. They used EfficientNetB4 as the encoder to extract feature data. They also use attention gates in the skip structure to draw attention to the feature data and get rid of the irrelevant feature answers. The suggested approach was then put up against four established models, including FCN, U-Net, Attention U-Net, and Attention ResU-Net. The suggested technique thus outperformed the benchmarks on five measures, as a result, the suggested EAR-U-Net might improve feature learning capabilities, enrich semantic information, and concentrate on small-scale hepatic information.

3. Other Neural Network Approaches

Jain et al. in [19] The transverse part of the common carotid artery was proposed to be localized using a novel approach in this research (CCA). In the Convolutional, fully connected, and pooling three layers of the rapid region convolutional neural network (FRCNN)-based localization technique —are employed in a stack. These ordered layers comprised the Object class detection network (OCDN) and region proposal network (RPN). Additionally, they received a result as a bounding box and a prediction score centered on the CCA

Author	Year	Image Modality	Canonical Task	Method/Model	Evaluation Metrics
B. Behboodi et. al. [1]	2019	Ultrasound Imaging	Segmentation	U-Net	DSC=0.2+0.1; F2=0.2+0.1
Amiri. M et. al. [4]	2020	Ultrasound Imaging	Segmentation and Augmentation	Two Stage U-Net	Dice < 70%
J. Ding et.al [5]	2019	Ultrasound Imaging	Segmentation	ReAgU-Net	mIoU = 0.788; DSC=0.869; Precision=0.873; Recall=0.86s
M. Xie et. al. [6]	2020	Ultrasound Imaging	Segmentation	Two Novel Convolutional U-Net	DICE; Accuracy=82.7
Meshram NH et. al. [7]	2020	Ultrasound Imaging	Segmentation	Dilated U-Net	Dice=0.55 [Automatic] Dice=0.84 [Semi-Automatic]
J. Li et. al. [8]	2021	X-ray, ultrasound, MRI images	Segmentation	Multi Scale Fusion U-Net	DSC=0.9535; Precision=0.934; Recall=0.9421; IOU=0.9112; 0.0694 FPs/Image
M. Xie et. al. [9]	2019	Ultrasound Imaging	Segmentation	CNN - U-Net	Accuracy=94.3; Cross-Validation Accuracy=96.6
Y. Li et. al. [10]	2021	Ultrasound Imaging	Segmentation	Light Weight U-Net	Dice =0.928
W. Yu et. al. [11]	2019	CT Scan Imaging	Segmentation	3D Residual U-Net	Dice = 0.69
M. Jiang et. al. [12]	2020	Ultrasound Imaging	Segmentation	3DUS U -Net (UNet+SAN)	DSC = 67.5; IoU = 0.53
Z. Zhou et. al. [13]	2020	Ultrasound Imaging	Segmentation	U-Net++	Dice, IoU
H. Li et. al. [14]	2020	CT Scan Imaging	Segmentation	EAR U-Net	Dice=0.9595; VOE=7.77+1.42 MSD=35,36mm

Fig: Comparison Table

cross-section. The convolutional neural network's Tuned features are produced by repeating training for 30, 200, and 2000 epochs. After 2000 epochs, they reach an accuracy of 95% for validation.

C. Azzopardi et al. in [20] Deep convolutional networks were recommended for use in the transverse and longitudinal carotid ultrasound images. to automatically segment the media-adventitia border. They also proposed employing encoder-decoder convolutional structures to apply the network to ultrasonic data, allowing for end-to-end training for pixel-wise categorization. They assessed the network's performance while using different topologies, depths, and filter sizes. Then it was demonstrated that the suggested network topology and the data fusion produced better segmentation results than cutting-edge methods.

Abd-Ellah et al. in [21] For the purpose of diagnosing CCA illness, a unique Computer-Aided Diagnosis (CAD) system has been created. by them. The four phases of their innovative CAD system are called: measurement of the intima-media thickness (IMT), segmentation, localization, and the CCA's rating as normal or abnormal Using a deep learning strategy known as a faster regional proposal convolutional neural network (Faster R-CNN), the CCA has been positioned precisely in the transverse section images. The CCA longitudinal portion has been classified as either normal or pathological using transfer learning from the pre-trained convolutional neural network (CNN) on AlexNet. The classification step received a perfect score for accuracy, sensitivity, and specificity using a variety of assessment parameters. The localization method's CCA detection accuracy was 97.5%.

M. H. Yap et al. in [22] To employ the techniques used for breast ultrasound lesion identification, this paper proposed a combination of three separate techniques— a transfer learning, a U-Net, and a patch-based LeNet strategy using a pre-trained FCN-AlexNet—as well as deep learning methodologies. Four cutting-edge lesion detection algorithms are compared to the other three (i.e., Rule-based Region Ranking, Multifractal Filtering, Deformable Part Models, and Radial Gradient Index). A comparison and contrast of two datasets of conventional ultrasound images obtained from two different ultrasound devices are also included in this research. When applied to both datasets, the deep learning algorithms show a general improvement in F-measure, True Positive Fraction, and False Positives per picture.

R. Zhou et al. in [23] Plaques from 2D carotid ultrasound images have been proposed to be segmented using the UNet++ Ensemble method, which was trained on three small datasets. and tested on his 44 subjects in the SPARC dataset. And various techniques are considered to measure the performance of the algorithm like DSc, ICC, CoV, and Pearson correlation. And the dice value for the algorithm was around 83-85% and the CoV of the algorithm is around 6.83%.

C. Azzopardi et al.in [24] proposed a completely automatic segmentation technique in a revolutionary Deep Neural Network in this paper, as well as its use in identifying media-advertising and lumen-intima boundaries. They created The Network's Stochastic Gradient Descent optimization is extended to include a new geometrically restricted objective function, which is tailored to the current situation.

Yuan et al. in [25] created a three-step framework that is totally automatic for segmenting the liver and abdomen CT with contrast-enhanced tumor imaging. Deep fully convolutional-deconvolutional neural networks (CDNN) are the foundation of the hierarchical structure they proposed. For liver fine segmentation, three CDNN models were used: a deeper CDNN model (CDNN-II) with doubled feature channels in each layer; tumor segmentation using the CDNN-II model with the increased liver region as an extra input feature; and liver localization using a straightforward CDNN model (CDNN-I).

G. Wang et al. in [26] provide a brand-new deep learning-based interactive segmentation system to deal with these issues by adding CNNs into a segmentation process that is based on bounding boxes and scribbles. A CNN model can be fine-tuned to become responsive to a particular test image, either supervised (with extra user interactions) or unsupervised (without them) (with additional scribbles). For the fine adjustment, they also provide a weighted loss function that takes network- and interaction-based uncertainty into account. Compared to conventional interactive segmentation approaches, their approach produces accurate results with fewer user engagements and less user time.

Gu R et al [27] paper, made considerable CNN's usage of various attention architectures and presented the CA-Net, a thorough focus-based CNN for further information precise and understandable segmentation of medical images. They first suggested a shared spatial attention module that would direct the network's attention toward the first row. The most important feature channels are then shown, and a novel channel attention module is proposed to alter the channel-wise functional responses. Additionally, they suggested a scale attention module, which is a CNN, that subtly emphasizes the most important feature maps across many scales modifying the dimensions of things.

Oktay O et al [28] presented a brand-new image analysis framework that trains neural network (NN) models using autoencoder (AE) and T-L networks as regularizes. The regularized model that has been proposed can be thought of as an application-specific training goal. In the event that the images are corrupted and contain artifacts, the experimental results demonstrate that the most recent NN models can benefit from the learned priors.

S. Sudha et al.in [29] The extraction of RoI is given more focus in this article since it contains the most important data regarding the image. Accurate RoI segmentation facilitates the categorization of abnormal symptoms while enhancing retrieval efficiency. Convolutional neural networks have been used in this study to automatically segment RoI in carotid artery ultrasound pictures and other medical imaging modalities (CNNs). Here, a comparison is made between the results obtained from the proposed network and with already existing SVM and radial basis function are two examples of machine learning techniques (RBF).

A. S. Pramulen et al. in [30] non-local means-based speckle filtering using the U-Net architecture was used in this work using ultrasonography, to distinguish the Carotid Artery picture (NLMBSF). The dataset has been split into two sections: one using NLMBSF and the other without using NLMBSF. Following the instruction on creating a U-net model, the outputs of the training data model were examined for the highest Accuracy.

D. Perdios et al.in [31] For the purpose of enhancing radio-frequency ultrasound (US) images, proposed a strategy that was inspired by the well-known U-Net architecture and was based on a convolutional neural network (CNN). For the purpose of enhancing images reconstructed from a single plane wave (PW) in sonification, the proposed strategy makes use of a convolutional neural network that has been exclusively trained on a simulated dataset. The numerical and the plane wave imaging challenge's in vivo data are used to evaluate three versions of the proposed architecture. They demonstrated the viability of the proposed strategy in real-time settings.

D. Mishra et al.in [32] created an attentional deep supervision fully convolutional neural network (FCNN) for ultrasound image segmentation that is automatic and precise. Here, The FCNN is deeply supervised in a subproblem-specific manner. which is the main contribution to this work. The suggested network is initially examined for the segmentation of blood vessels in liver pictures. It produces the F1 score, mIoU, and dice index with a value of 0.83, 0.83, and 0.79, respectively. Additionally, a dice index is produced by the proposed network in the lumen segmentation, with an index value of 0.91.

4. Conclusion

In this survey, we intended to explore various methods of Image Segmentation using U-Net and its forks, as well as other neural networks as models for deep learning include widely used for image segmentation in the medical field. So, we studied the uses of various U-Net variations in a legion of medical imaging modalities such as CT imaging, Ultrasound imaging, and MRI imaging.

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