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Attention U-Net Based Ultrasound Nerve Segmentation with Efficient Net Classification

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***Abstract:** Ultrasound imaging is commonly used to identify and study peripheral nerves, but image quality issues such as noise, low contrast, and unclear structures make accurate analysis difficult. To address this, a deep learning-based approach is proposed that combines preprocessing, segmentation, and classification. CLAHE and SRAD are first applied to improve image quality by enhancing contrast and reducing noise. Then, an Attention U-Net model is used to detect the nerve region by focusing on important areas while reducing background interference. The detected region is extracted and passed to an EfficientNet-B0 model for classification. The system is trained and tested on the Kaggle ultrasound nerve dataset with around 5,600 images. The results show improved Dice score, IoU, and classification accuracy compared to existing methods, indicating that the proposed method provides a reliable and efficient solution for automated ultrasound nerve analysis.*
***Keywords:** Attention U-Net, Ultrasound Nerve Segmentation, EfficientNet-B0, CLAHE–SRAD Preprocessing, Medical Image Analysis*

I. INTRODUCTION

Identifying nerves in ultrasound images is important for medical uses like giving anesthesia, managing pain, and helping in surgeries [1]. Ultrasound is commonly used because it shows images in real time, is easy to carry, and costs less than MRI or CT scans. However, these images are not always clear. They often have noise, low contrast, shadows, and differences in how nerves appear in different patients. Because of this, it becomes difficult to automatically detect and segment nerves correctly [9].

Usually, doctors look at these images and identify nerves manually, which takes time and can vary from person to person. In some places, skilled experts may not always be available. To solve this, deep learning methods are now used to make the process automatic and more reliable [19]. Earlier methods used basic image processing and manual features, but newer models like U-Net can learn directly from the data. Still, U-Net may miss small or unclear nerve regions. To improve this, attention-based models are used so the system can focus more on important areas. In this work, a simple pipeline is used that includes preprocessing, segmentation, region extraction, and classification to improve nerve detection in ultrasound images.

Figure1: Clinical ultrasound-guidedperipheral nerve assessment

II. LITERATURE REVIEW

Many researchers have worked on detecting nerves in ultrasound images using deep learning. Ramaswamy et al. [1] developed a model called HPyS-Net, which combines different techniques to improve accuracy. It gave good results but still depended on manually designed features. Another important model is U-Net [2], which is widely used for medical image segmentation because it works well even with less data. Later, Attention U-Net [3] improved this model by helping it focus more on important regions and ignore unwanted background areas. EfficientNet [4] is another useful model that gives good accuracy while using fewer resources, making it suitable for real-world applications. TransUNet [23] combines CNN and Transformer models to capture both local and global features.

Other models like RFF-U-Net [9] and Attention-VGG16-UNet [13] also showed good results in nerve segmentation, but they still have some limitations, such as difficulty handling complex cases or lack of clear explanations. Some studies [12] also faced problems due to differences in nerve shapes in different patients. For improving image quality, techniques like SRAD [5] help reduce noise while keeping important edges, and filters like Wiener filtering [24] are also used. Modern models such as Transformers [21] and ResNet [20] have further improved deep learning performance. From all these studies, it is clear that combining good preprocessing with advanced models can give better results in ultrasound nerve analysis.

III. METHODOLOGY

A. Overview

The The proposed system works in a step-by-step process with four main stages. Each stage handles a specific task, such as improving image quality, finding the nerve area, extracting the important region, and finally classifying it.

Unlike earlier methods like HPyS-Net [1], which use manually designed features, this system uses deep learning models to learn directly from the data. It uses Attention U-Net for segmentation and EfficientNet-B0 for classification. Because it is trained on a larger dataset, it can give better and more reliable results.

B. Dataset

The system is trained and tested using the Kaggle Ultrasound Nerve Segmentation dataset [7], which contains about 5,600 high-quality ultrasound images of the brachial plexus nerve area. Each image has a corresponding mask created by experts to show the exact nerve region. The dataset is divided into training, validation, and testing sets in the ratio of 80:10:10. Compared to the smaller Nerve-UTP dataset (691 images) used in [1], this dataset is larger and more varied, which helps the model learn better and give more reliable results.

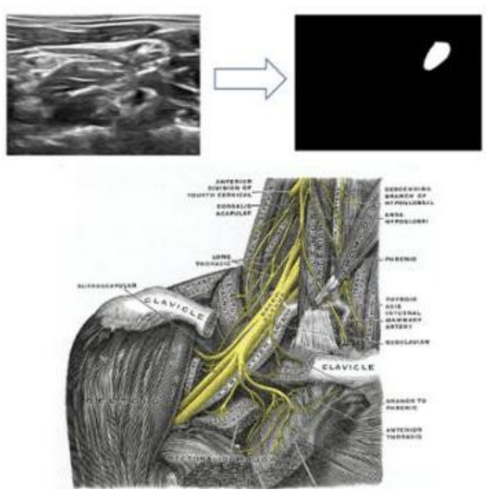

Figure2: Sample ultrasound image (left) and corresponding binary segmentation mask (right) from the Kaggle dataset [7]

Attribute	Details
Total Images	~5,600 ultrasound scans

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Annotation Type	Expert-annotated binary segmentation masks
Train / Val / Test Split	80% / 10% / 10%
Task Complexity	High speckle noise, low contrast, inconsistent anatomy
Image Resolution	High-resolution B-mode ultrasound

Table 1: Kaggle Ultrasound Nerve Dataset Summary

C. Preprocessing: CLAHE–SRAD Hybrid (M1)

The preprocessing step improves the quality of ultrasound images before segmentation by using two techniques. First, CLAHE [6] is used to increase the contrast in different parts of the image. It works on small sections of the image and limits how much the contrast is increased, so that noise is not over-enhanced. This helps to make the boundaries of the nerve more clear. This is different from the Adaptive Wiener Filter (AWF) [1], which mainly focuses on reducing noise.

After that, SRAD [5] is applied to further improve the image. It reduces speckle noise while keeping important edges, such as nerve boundaries, clear. Together, CLAHE and SRAD improve the image by increasing contrast and reducing noise, which helps in better and more accurate segmentation.

D. Segmentation: Attention U-Net (M2)

The segmentation part uses the Attention U-Net model [3]. This model includes attention gates that are added to the connections between the encoder and decoder. The encoder reduces the image size step by step to learn important features at different levels, while the decoder increases the image size again to produce the final segmented output.

The attention gates help the model focus more on important areas, such as the nerve region, and give less importance to background areas. This is better than TransUNet-based methods [1] because it can handle different nerve shapes and sizes more easily without using complex transformer models. It also reduces computation time and improves the accuracy of detecting nerve boundaries.

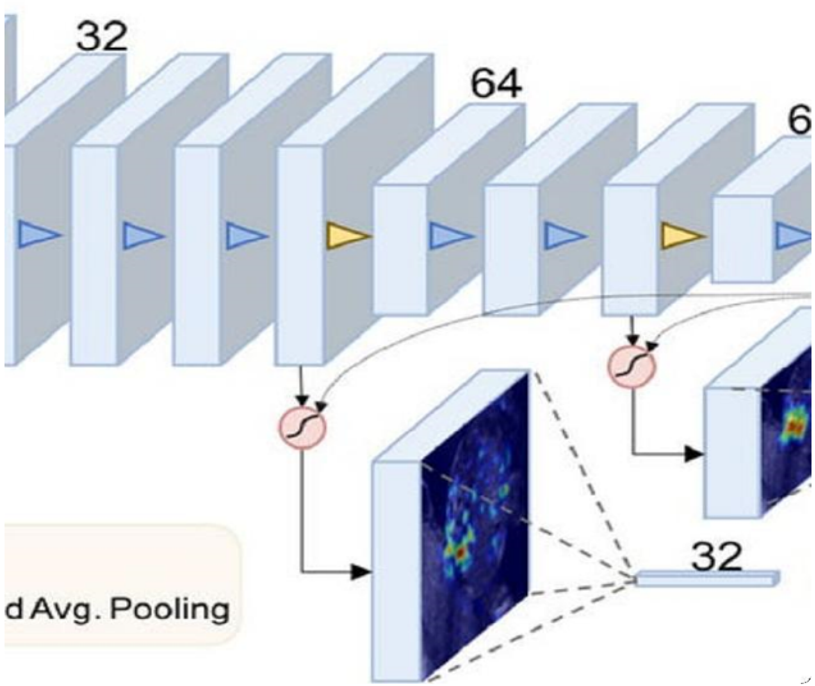

Figure3:Attention U-Net architecture with attention gate mechanism for saliency-aware nerve localization [3]

E. ROI Extraction (M3)
After segmentation, the predicted mask is used to find the region of interest that contains the nerve. The non-zero pixels in the mask help identify the boundary of this region, and the same area is cropped from the preprocessed image. This step removes unnecessary background parts and reduces the input size for the EfficientNet-B0 classifier. As a result, the model focuses only on the important nerve region, which helps improve classification accuracy.

F. Classification: EfficientNet-B0 (M4)
The extracted ROI images are used as input to the EfficientNet-B0 model for final classification. Unlike earlier methods that rely on manually designed features, EfficientNet-B0 learns useful features directly from the data during training. It uses a scaling method to balance depth, width, and input size, which helps achieve good accuracy with fewer parameters. For classification, a global average pooling layer is used, followed by a sigmoid activation function for binary classification.

Figure4: EfficientNet-B0 architecture showing 7 MBConv blocks with compound scaling

G. Training Configuration
All modules are implemented in Python using TensorFlow [28] and Keras [29]. The Attention U-Net model is trained using a combination of binary cross-entropy and Dice loss to improve segmentation performance. To make the model more general, data augmentation techniques such as horizontal flipping, rotation, elastic deformation, and brightness adjustment are applied. The EfficientNet-B0 model is fine-tuned using binary cross-entropy loss with the Adam optimizer (learning rate = 0.001). Both models are trained on a GPU system, and early stopping is used to prevent overfitting.

IV. RESULTS AND DISCUSSION

A. Segmentation Performance
The Attention U-Net gives better segmentation results compared to the standard U-Net model [2]. The use of attention gates helps the model focus on the nerve area while reducing background noise, leading to a Dice score of 0.88 and an IoU of 0.81. The model works especially well for images where the nerve is small or has an irregular shape, where the standard U-Net often fails to detect the region properly.

Method	Dice Coefficient	IoU Score
Standard U-Net [2]	0.71	0.63
Attention U-Net (Proposed)	0.88	0.81

Table 2: Segmentation Performance Comparison

B. Classification and Overall Performance
The EfficientNet-B0 classifier [4], which uses the extracted ROI nerve regions, achieves an accuracy of 0.95. This twostep process (segmentation followed by classification) helps reduce errors from the segmentation stage and improves the overall reliability of the system. Compared to the HPyS-Net model [1], which achieved 91.8% accuracy using manually designed features, the proposed method gives better results by learning features directly from the segmented nerve images.

Figure 5: Proposed system performance — Dice Coefficient: 0.88, IoU: 0.81, Total Accuracy: 0.95

C. Comparison with Existing Methods

The proposed system performs better than many existing methods. The use of attention helps detect nerve boundaries more accurately compared to RFF-U-Net [9]. It also gives more stable results than standard CNN-based methods [10][11] because it includes preprocessing and segmentation steps. In addition, the two-stage approach (segmentation followed by classification) makes the system more reliable than single-stage methods [13][14], which is useful for real clinical applications.

Method	Accuracy / Dice	Key Limitation
HPyS-Net [1]	91.8%	Handcrafted features, smaller dataset
RFF-U-Net [9]	84.6%	No explainability, limited 3D
Mask R-CNN [12]	89.9%	Brightness augmentation not considered
Standard U-Net [2]	0.71 Dice	No spatial attention
Attention U-Net (Proposed)	0.88 Dice / 0.95 Acc	Proposed method

Table 3: Comparison with Existing Methods

V. CONCLUSION

In this work, a deep learning system is developed to automatically find and classify nerves in ultrasound images. Earlier Methods like HPyS-Net [1] used manually designed features, which limited their performance. To solve these problems, this system uses four steps: CLAHE–SRAD preprocessing [5][6], Attention U-Net for segmentation [3], ROI extraction, and EfficientNet-B0 for classification [4]. This helps reduce noise, improve contrast, and handle differences in nerve shapes.

The use of attention in the U-Net model helps the system focus better on the nerve region, giving better results than the normal U-Net model [2]. The system achieves a Dice score of 0.88, IoU of 0.81, and accuracy of 0.95 on the Kaggle dataset [7]. Since it learns features directly from the data instead of using manual features like GLCM, LOOP, and LVP, it works better and can handle different cases more easily.

In the future, this work can be improved by using 3D ultrasound data, adding explainable AI methods to understand how the model makes decisions, and testing the system in real hospitals. It can also be extended to identify different types of structures, such as nerves and arteries.

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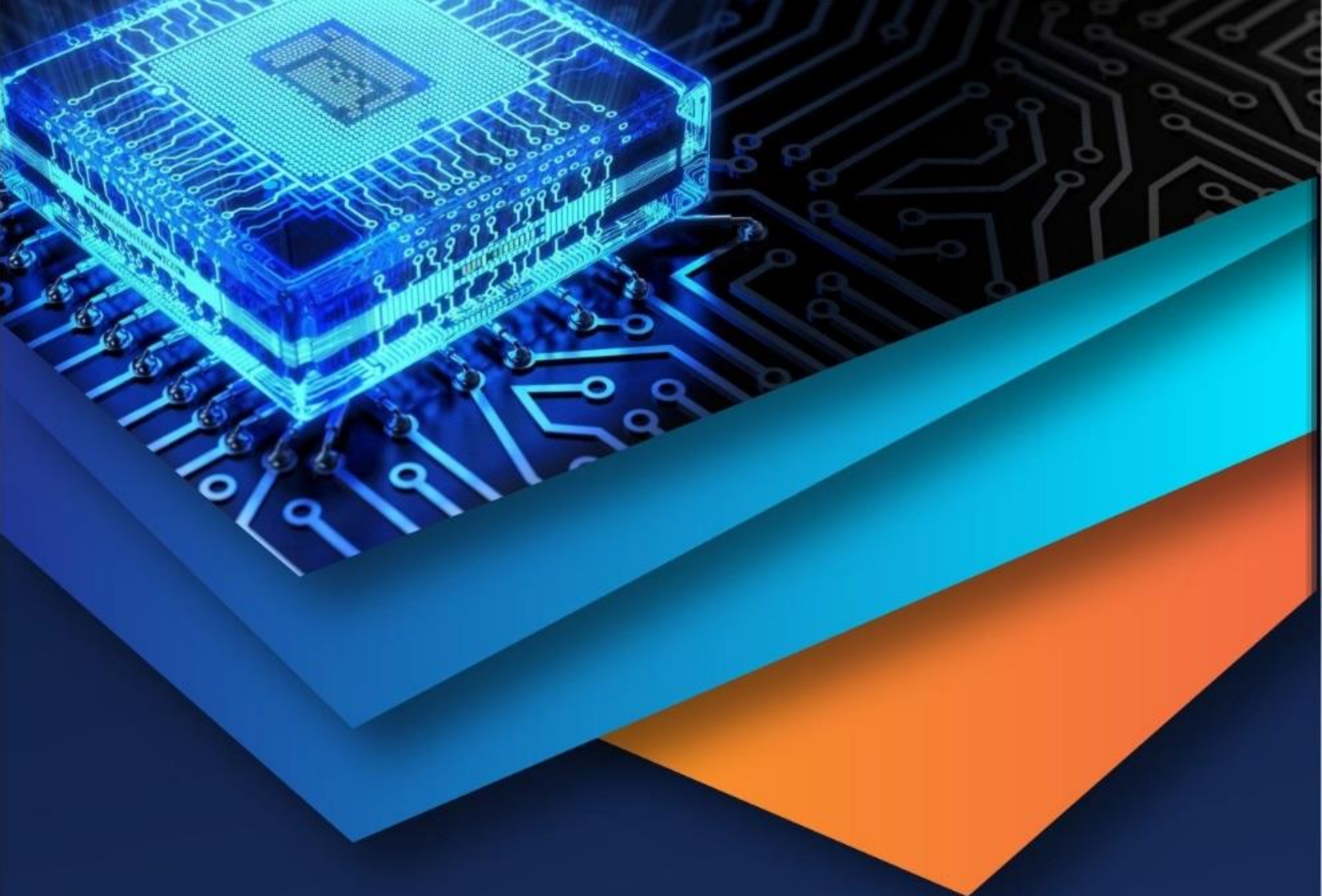

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