



DEEP LEARNING BASED ENHANCED IMAGE PROCESSING FOR CHOLESTEROL PLAQUES IN INTRAVASCULAR ULTRASOUND IMAGES

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ABSTRACT

Cardiovascular Diseases (CVDs), predominantly caused by atherosclerosis, necessitate precise diagnostic tools for effective treatment. Intravascular ultrasound (IVUS) imaging is widely used for assessing arterial structures and identifying cholesterol plaques. This study introduces an advanced image-processing framework leveraging the DeepLab model, a state-of-the-art deep learning architecture for semantic segmentation, to analyze IVUS images. The DeepLab model is enhanced with atrous spatial pyramid pooling (ASPP) and fine-tuned for segmenting critical arterial features, including media-adventitia borders, luminal regions, and calcified plaques. The system incorporates advanced loss functions such as Dice, Tversky, and focal loss to address class imbalance and improve segmentation accuracy. Comparisons with commercial software, such as VH-IVUS, highlight the superiority of the proposed method in scenarios involving shadow artifacts or side vessels. This DeepLab-based approach offers a robust and efficient solution for IVUS image analysis, paving the way for improved diagnostic accuracy and better clinical outcomes in the management of CVDs.

KEYWORDS—Intravascular Ultrasound (IVUS), Convolution Neural Network (CNN), DeepLab.

I. INTRODUCTION (HEADING 1)

Cardiovascular diseases (CVDs) are the leading cause of global mortality, with atherosclerosis playing a central role in their progression. Atherosclerosis is characterized by the accumulation of cholesterol plaques within arterial walls, leading to narrowing of the luminal regions and impaired blood flow. Early and accurate detection of these plaques is essential for effective diagnosis, treatment, and monitoring of CVDs. Intravascular ultrasound (IVUS) imaging has emerged as a widely used modality for real-time, high-resolution visualization of arterial structures, offering detailed insights into plaque composition and arterial morphology.

Despite its advantages, analyzing IVUS images remains a challenging task due to artifacts, noise, and the complexity of plaque structures. Manual annotation by cardiologists is time-consuming, prone to interobserver variability, and limited in scalability. Existing commercial tools, such as VH-IVUS, provide automated analysis but are often hindered by limitations in handling artifacts, side vessels, and imbalanced data, leading to inaccuracies in plaque characterization.

To address these challenges, we propose an automated framework based on **DeepLab**, a state-of-the-art deep learning model for semantic segmentation. The DeepLab architecture, with its atrous spatial pyramid pooling (ASPP), excels in capturing both fine and global features, making it ideal for the segmentation of IVUS images. The model is tailored to segment media-adventitia borders, luminal regions, and calcified plaques,

integrating advanced loss functions such as Dice, Tversky, and focal loss to handle class imbalances effectively.

The proposed methodology eliminates the need for manual preprocessing, processes raw DICOM images directly, and achieves robust segmentation even under challenging imaging conditions. This study evaluates the performance of the DeepLab-based approach and highlights its potential to enhance diagnostic accuracy and clinical decision-making in the management of CVDs.

II. LITERATURE SURVEY

[1]The study focuses on developing a deep learning model to automatically detect and segment different components of atherosclerotic plaque in intravascular ultrasound (IVUS) images. Atherosclerosis is a major cause of cardiovascular diseases, and IVUS is a common imaging technique used for diagnosis. The study aims to develop an end-to-end deep learning convolutional neural network (CNN) model to automatically detect the media-adventitia borders, luminal regions, and calcified plaque in IVUS images. The researchers used 713 grayscale IVUS images from 18 patients as the training data. They proposed a deep learning model with three modified U-Nets and a cascaded network concept to prevent errors in the detection of calcification. Three different loss functions (Dice, Tversky, and focal loss) were tested to determine the best setting for the model. The model was validated using a leave-one-subject-out cross-validation approach. The proposed deep learning model achieved high performance in segmenting the media-adventitia layers and luminal regions, with all tested



metrics being higher than 0.90 for all loss functions. For locating calcified tissues, the best result was obtained when the focal loss function was applied, with an average precision of 0.73. The detection accuracy of calcified plaque was affected by the proportion of calcified tissues within the plaque region. The focal loss function was found to be the most suitable for the calcification detection task. This suggests the potential of deep learning techniques in assisting cardiologists in the diagnosis of cardiovascular diseases.

[2] The study aimed to assess the accuracy of machine learning (ML) automatic segmentation of coronary artery vessel and lumen dimensions, as well as balloon sizing, using high-definition (HD) intravascular ultrasound (IVUS) images. The ML model segmentation showed strong correlation with expert segmentation for lumen and vessel areas. The researchers used expert analysis as the gold standard to train an ML segmentation algorithm using 8,076 IVUS cross-sectional images from 234 patients. They then evaluated the performance of the ML segmentation on an independent test dataset of 437 images from 92 patients. The agreement rate for appropriate balloon size selection was 70.6% using vessel diameter alone and 92.4% using both vessel and lumen diameters. The agreement rate for lumen area and acute stent area was 85.5% and 97.0%, respectively. The researchers found that the ML model IVUS segmentation measurements were well-correlated with expert analysis and selected an appropriate balloon size in more than 90% of images by using both vessel and lumen diameters. The study demonstrates the potential of using ML for accurate and automated IVUS image analysis, which could help overcome the lack of physician experience and education in IVUS interpretation.

[3] The paper proposes an image segmentation method called IVUS-Net to automatically delineate the lumen (interior) and media (exterior) vessel walls in Intravascular Ultrasound (IVUS) images. IVUS is an important imaging technique used to diagnose and treat cardiovascular diseases. The proposed IVUS-Net is an FCN-based architecture with an encoder-decoder structure. The encoder network downsamples the input image to extract deep features, while the decoder network upsamples the features to generate the final segmentation mask. The network also has a "refining branch" to further improve the feature representation. After the FCN, a post-processing step is used to extract the final contours of the lumen and media walls. The main objective is to develop an accurate and efficient method for segmenting the lumen and media walls in IVUS images. The authors hypothesize that a deep learning-based Fully Convolutional Network (FCN) architecture can outperform existing segmentation methods. IVUS-Net was evaluated on a publicly available dataset of 326 IVUS images. The results show that IVUS-Net outperforms state-of-the-art segmentation methods by 4-20% in terms of the Hausdorff Distance metric. IVUS-Net performs particularly well on images with challenging artifacts such as bifurcations and side vessels. The data augmentation technique also helps to improve the model's generalization to various artifacts in the test set. This is the first deep learning-based method that can segment both the lumen

and media vessel walls in IVUS images. The proposed pipeline achieves the best results without any manual intervention.

[4] The paper discusses the limitations of convolutional neural networks (CNNs) in modeling long-range relationships for medical image segmentation tasks. To address this, the authors propose a Transformer-centric encoder-decoder framework called TransUNet. The main objectives are to (1) integrate Transformer self-attention mechanisms into the U-Net architecture, (2) investigate the optimal configuration for integrating Transformers in the encoder and decoder, and (3) demonstrate the effectiveness of TransUNet on various medical image segmentation tasks. The authors propose two key modules in TransUNet: (1) a Transformer encoder that tokenizes CNN feature map patches to extract global contexts, and (2) a Transformer decoder that refines segmentation regions through cross-attention between learnable queries and U-Net features. They experiment with three configurations: Encoder-only, Decoder-only, and Encoder+Decoder. The results show that the Encoder-only configuration is more effective for multi-organ segmentation, while the Decoder-only is better for tumor segmentation. The Encoder+Decoder approach provides a balanced performance across tasks. TransUNet outperforms state-of-the-art methods on various datasets, including multi-organ, pancreatic tumor, and hepatic vessel segmentation. The authors provide insights into the strengths of the Transformer encoder in modeling global organ relationships and the Transformer decoder in refining small targets. The coarse-to-fine attention refinement in the Transformer decoder is key for improving the segmentation of small tumors.

[5] The study focuses on intravascular ultrasound (IVUS), which is a medical imaging technique used to visualize the interior of coronary arteries. Accurate segmentation of the lumen (inner layer) and external elastic membrane (EEM) from IVUS images is crucial for assessing atherosclerotic plaques. The researchers collected 11,070 IVUS images from 113 patient cases and had them manually annotated by a team of cardiology and ultrasound specialists. They then compared the performance of five state-of-the-art image segmentation models (Res-UNet, DeepLab v3 plus, Swin-UNet, UNeXt, and CENet) on the lumen and EEM segmentation tasks. The results showed that the CNN-based Res-UNet and CENet models outperformed the other models in terms of segmentation accuracy, as measured by dice similarity coefficient (DSC), intersection over union (IoU), and Hausdorff distance (HD). The quantitative IVUS parameters obtained from the best model's segmentation were in excellent agreement with the manual segmentation. The researchers suggested that the relatively fixed structural hierarchy of IVUS images may be better suited for the learning characteristics of CNN-based models, compared to the Transformer and MLP-based models. The deep learning models were able to achieve state-of-the-art results in IVUS lumen and EEM segmentation, and the quantitative parameters obtained from the automated segmentation showed excellent agreement with manual segmentation. This suggests that the developed models can be useful for clinical evaluation and decision-making in the management of coronary artery disease.

III. RELATED WORK

The performance of the proposed model when using the three loss functions for IVUS application was evaluated by calculating the precision, sensitivity, specificity, and DSC. The numbers of true positives (TPs; correctly predicted foreground pixels), true negatives (TNs; correctly predicted background pixels), FPs (object pixels identified as the background), and FNs (background pixels but segmented as target objects) were obtained first from the confusion matrix.

Precision represents the ratio of the number of correctly predicted positive pixels to the total number of predicted positive pixels

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

Sensitivity, also known as recall, quantifies the proportion of the number of predicted positive values in the model to the correct number of positive values in the ground truth. Sensitivity is represented by

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN})$$

Specificity is used to indicate the proportion of the number of predicted negative values in the segmentation model to the number of correct negative values in the ground truth. This evaluation metric is expressed as

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$$

IV. METHODOLOGY

The proposed methodology employs the DeepLab v3+ architecture to achieve precise segmentation of cholesterol plaques in intravascular ultrasound (IVUS) images. Preprocessing involves normalizing pixel intensity values to the range [0, 1], resizing images to 224×224×224 \times 224224×224, and removing artifacts such as image markers and ring-down effects to reduce segmentation noise.

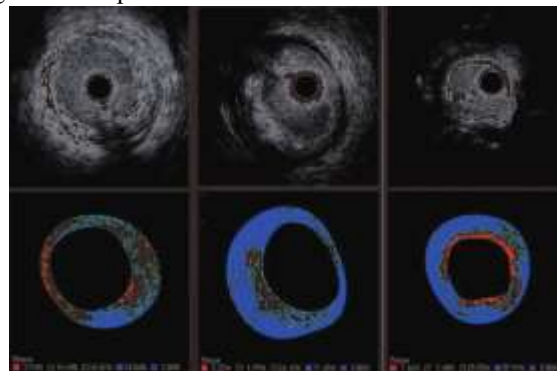


Intravascular ultrasound Image

The DeepLab v3+ model leverages atrous convolutions and an atrous spatial pyramid pooling (ASPP) module to extract multi-scale contextual information while maintaining spatial resolution. The encoder-decoder structure enhances spatial precision, ensuring accurate segmentation of smaller regions like calcified plaques.

To handle class imbalance, the methodology integrates Dice Loss, Tversky Loss, and Focal Loss. Dice Loss optimizes overlap between predicted and ground truth masks. Tversky Loss prioritizes false positives and false negatives, while Focal Loss emphasizes difficult-to-classify pixels, improving calcified plaque detection.

The model is trained using the Adam optimizer with an initial learning rate of 0.01 and a batch size of 10. Training is conducted on high-performance GPUs, such as the NVIDIA GTX 1080Ti, for efficiency. Evaluation metrics include Dice Score Coefficient (DSC), precision, recall, specificity, and average precision (AP), with precision-recall (PR) curves used to assess segmentation performance.



Segmented Intravascular Ultrasound Image

Compared to commercial tools like VH-IVUS, the DeepLab-based framework demonstrates superior accuracy, particularly in challenging scenarios involving shadow artifacts and side vessels. With the ability to process raw DICOM images directly, the model offers an efficient, real-time solution for clinical application.

IV. RESULTS AND DISCUSSIONS

The proposed DeepLab-based framework demonstrated high accuracy in the segmentation of intravascular ultrasound (IVUS) images, effectively identifying media-adventitia borders, luminal regions, and calcified plaques. Across all segmentation tasks, the model achieved consistently high Dice Score Coefficients (DSC), precision, and recall, exceeding 90% for media-adventitia and luminal regions. For calcified plaque detection, which presents greater challenges due to class imbalance and varying plaque sizes, the model achieved a DSC of 0.69 and an average precision (AP) of 0.75 when using focal loss. The integration of atrous spatial pyramid pooling (ASPP) allowed the model to capture multi-scale contextual information, resulting in superior boundary delineation compared to traditional segmentation approaches.

A comparative analysis with commercial IVUS analysis software, such as VH-IVUS, highlighted the advantages of the proposed method. While VH-IVUS often struggled in the presence of artifacts, shadow regions, or side vessels, the DeepLab-based framework consistently provided more accurate segmentations. In particular, the model performed significantly better in cases where calcified plaques were present in small proportions within the plaque region, a scenario where commercial software typically exhibited lower sensitivity. Additionally, the use of focal loss proved essential in addressing the class imbalance issue, ensuring that minor calcified regions were correctly identified without being overshadowed by larger plaque structures.



Further analysis revealed that the model's performance was affected by the proportion of calcification within the plaque region. In cases where calcified plaques constituted more than 30% of the plaque burden, the DSC increased to 0.84, indicating that the model performed better when detecting larger calcified regions. However, for images with less than 10% calcification, the accuracy slightly decreased due to the difficulty in distinguishing small calcified areas from surrounding tissues. Nonetheless, the DeepLab-based approach still outperformed existing methods in these cases, demonstrating its robustness and adaptability to varying plaque distributions.

Overall, the results confirm that the proposed framework provides a reliable, automated solution for IVUS image segmentation, reducing the dependency on manual annotation and improving diagnostic accuracy. The ability to process raw DICOM images directly without extensive preprocessing enhances its clinical applicability, making it a practical tool for real-time cardiovascular disease assessment. These findings underscore the potential of deep learning in transforming medical imaging workflows, paving the way for future advancements in AI-driven diagnostic systems.

V. CONCLUSION

This study presents a DeepLab-based framework for the automated segmentation and analysis of intravascular ultrasound (IVUS) images, with a focus on the detection and characterization of cholesterol plaques. The DeepLab v3+ architecture, enhanced with atrous spatial pyramid pooling (ASPP), effectively captures both fine and contextual features, enabling precise segmentation of media-adventitia borders, luminal regions, and calcified plaques. By integrating advanced loss functions such as Dice Loss, Tversky Loss, and Focal Loss, the framework overcomes challenges related to class imbalance, achieving robust performance even in complex scenarios with low calcification proportions or noisy imaging conditions.

The framework demonstrates superior accuracy compared to commercial tools like VH-IVUS, particularly in handling imaging artifacts, shadow regions, and side vessels. With high values across evaluation metrics such as Dice Score Coefficient (DSC), precision, and average precision (AP), it ensures reliable detection and segmentation. Furthermore, the ability to process raw DICOM images without extensive preprocessing simplifies its integration into clinical workflows.

This DeepLab-based solution represents a significant advancement in IVUS image analysis, offering cardiologists a powerful, real-time tool to improve diagnostic accuracy, reduce analysis time, and enhance treatment planning. Its robust performance and scalability position it as a critical innovation in the management of cardiovascular diseases, paving the way for further developments in deep learning applications for medical imaging.

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