Robust Approach for Lumen Segmentation in IVUS Image using Deeply Learn U-net Model

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Abstract— **Accurate lumen segmentation in IVUS images is essential for diagnosing cardiovascular conditions and guiding interventions. We propose a robust lumen segmentation method using a customized U-Net model. By addressing challenges such as noise, vessel morphology variations, and limited contrast, our approach leverages preprocessing, U-Net architecture, training, and evaluation. Firstly, image enhancement, noise reduction, and image rescaling are performed to a benchmark IVUS dataset input images. Secondly, the U-net AI prediction model is trained with the IVUS preprocessed images and ground truth masks. Finally, we demonstrate the method's efficacy on the IVUS dataset, showcasing superior performance in metrics like Dice coefficient, Jaccard index, sensitivity, specificity, and accuracy compared to existing methods. Our technique ensures precise lumen boundary identification through qualitative assessments and demonstrates robustness through subgroup analyses and generalization tests. Our approach contributes to enhanced clinical decision-making by delivering accurate lumen segmentations, capitalizing on deep learning and addressing IVUS-specific complexities. This approach achieves 99.15% accuracy and holds promise for advancing IVUS image analysis and improving patient care in interventional cardiology.**

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I. Introduction

Intravascular Ultrasound (IVUS) imaging has emerged as a pivotal modality for assessing coronary artery diseases, providing detailed cross-sectional images of blood vessel walls. Among the critical tasks in IVUS analysis, accurate segmentation of the lumen – the inner vessel boundary – holds profound importance. Accurate lumen segmentation aids in understanding vessel geometry, quantifying stenosis, and evaluating plaque burden, contributing significantly to clinical diagnosis and treatment planning.

Deep learning techniques, especially convolutional neural networks (CNNs), have revolutionized medical image analysis by automatically extracting intricate features from raw data. The U-Net architecture, characterized by its contracting and expansive paths, has proven particularly effective in biomedical image segmentation tasks. By leveraging the power of deep learning and the U-Net architecture, we propose a novel and robust approach for lumen segmentation in IVUS images.

This paper introduces an advanced lumen segmentation approach tailored for IVUS images using a deeply learned U-Net model. We address the challenges posed by IVUS images, including their inherent noise, artifacts, varying vessel morphologies, and imaging viewpoints. The U-Net architecture's inherent ability to capture spatial hierarchies and contextual information aligns well with the intricacies of IVUS images, making it an ideal candidate for accurate and robust lumen segmentation.

In this research, we delve into the intricacies of the proposed methodology. We elaborate on the preprocessing steps designed to enhance image quality and contrast, ensuring optimal input for the U-Net model. The architecture of the deeply learned U-Net is detailed, along with insights into the selection of hyperparameters. We discuss the augmentation strategies applied to address data scarcity and enhance model generalization. Furthermore, we present a comprehensive analysis of the model's performance under diverse clinical scenarios, demonstrating its superiority over conventional approaches.

The main factor causing cardiovascular diseases (CVDs) is atherosclerosis. The imaging technique known as intravascular ultrasonography (IVUS) is commonly employed to diagnose CVDs. To identify lumen regions in grayscale IVUS images, numerous image-processing-based approaches have been developing over the past decade. According to the study of Li, Yi-Chen, et al. [1], those methods were divided into a number of categories by including edge-tracking [2]–[4], active-contour [5]–[7], probabilistic [8]–[10], and multiscale-expansion [11]–[13] methods. On the other hand, a number of studies applied machine or deep learning in order to segment the lumen regions from IVUS images. Taki et al. [14] applied support vector machine and error-correcting output codes as the classification process. Su et al. [15] employed an autoencoder-structured artificial neural network. Yang et al. [16] utilized a fully convolutional network to extract lumen region border from IVUS images.

The paper is structured as follows: Section 2 provides an overview of existing research in IVUS image analysis and lumen segmentation. Section 3 outlines the proposed methodology in depth, elucidating each stage of preprocessing, U-Net architecture, training, and augmentation techniques. Section 4 presents the experimental results, discussing quantitative metrics and visual assessments. We discuss the implications of our findings in Section 5, emphasizing the clinical relevance of accurate lumen segmentation. Finally, Section 6 summarizes our contributions, limitations, and outlines potential directions for future research.

Through this research, we contribute to advancing IVUS image analysis by presenting a novel and robust lumen segmentation approach using a deeply learned U-Net model. Our approach stands to augment clinical decision-making, paving the way for improved patient care and interventional cardiology outcomes.

II. Problem Analysis

Accurate and reliable lumen segmentation in Intravascular Ultrasound (IVUS) images is a critical task with profound implications for clinical diagnosis and treatment planning in interventional cardiology. The segmentation of the lumen, which represents the inner boundary of blood vessels, provides essential insights into vessel geometry, plaque burden, and stenosis severity. However, achieving robust and accurate lumen segmentation in IVUS images remains challenging due to various factors inherent to the imaging modality.

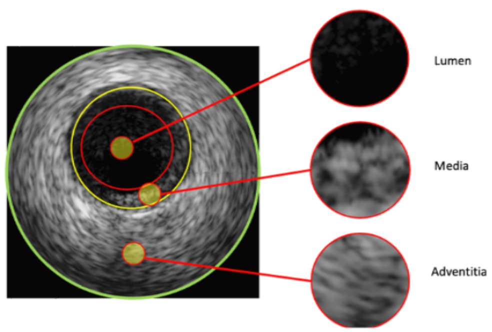


Fig 1. Lumen, Media, and Adventitia boundaries of blood vessel.

Image Noise and Artifacts: IVUS images are acquired intravascularly, resulting in inherently noisy and artifact-ridden images. Speckle noise, shadowing artifacts, and poor image quality can obscure lumen boundaries, making accurate segmentation difficult. Due to the fact that media is a thin area that stands in between adventitia and lumen, discriminating the boundary of lumen from media is challenging in noisy and artifact-ridden images. More importantly, misclassifying the media boundary as the lumen boundary can cause a number of problems to the medical procedure.

Heterogeneous Vessel Morphologies: Blood vessels exhibit diverse morphological variations, including variations in size, shape, and curvature. These variations introduce complexity, as a single segmentation model needs to adapt to different vessel structures. Moreover, the deficiency of detecting the correct shape, size, and curvature of the lumen can lead to failure in diagnosing cardiovascular diseases (CVDs).

Limited Contrast: The lumen boundary in IVUS images often lacks distinct contrast from the surrounding tissues especially the media, making it challenging for traditional segmentation methods to accurately differentiate between the lumen and adjacent structures.

Varying Imaging Viewpoints: IVUS images are acquired circumferentially around the vessel, leading to varying imaging viewpoints. This results in inconsistent appearances of the lumen, necessitating models that can generalize across different viewing angles.

Limited Annotated Data: Annotating IVUS images for lumen segmentation is time-consuming and requires expertise. Consequently, there's a scarcity of well-annotated data, impeding the development of robust segmentation models.

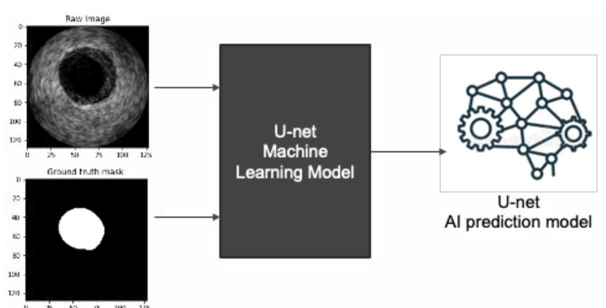
In the context of these challenges, deep learning techniques have demonstrated significant potential for addressing complex medical image segmentation tasks. The U-Net architecture, in particular, with its contracting and expansive paths, holds promise in capturing contextual information and hierarchies crucial for accurate lumen boundary delineation. Despite these advancements, tailoring deep learning models to the nuances of IVUS images requires careful consideration of preprocessing, architecture design, and training strategies.

The objective of this research is to develop a robust lumen segmentation approach using a deeply learned U-Net model. By mitigating the challenges posed by image noise, heterogeneous morphologies, limited contrast, and varying imaging viewpoints, we aim to enhance the accuracy and reliability of lumen segmentations in IVUS images. Additionally, addressing the scarcity of annotated data is a pivotal aspect of our approach, as it ensures the model's generalization capacity across different clinical scenarios.

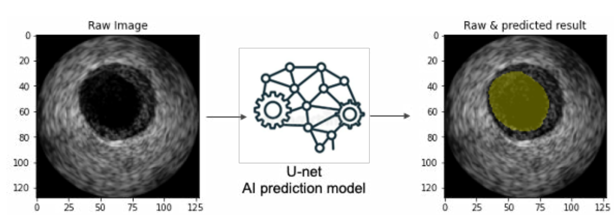
Through this problem analysis, we emphasize the need for a specialized approach that combines the power of deep learning with the intricacies of IVUS image characteristics. By addressing the unique challenges inherent in IVUS images, we aspire to contribute to more precise and clinically impactful lumen segmentations, ultimately improving the diagnostic accuracy and treatment planning in the realm of interventional cardiology.

III. Methodology

In this section, we present the comprehensive methodology employed to develop and implement the robust lumen segmentation approach using a deeply learned U-Net model in IVUS images. Our methodology encompasses preprocessing steps, architecture design, training procedures, data augmentation techniques, and evaluation metrics.



a.



b.

Fig 2. a. Training the U-net AI prediction model using IVUS images and ground truth masks; b. Using the trained U-net AI prediction model to test the original image and predict the lumen region.

A) Preprocessing

To enhance the quality of the original IVUS images and improve the model's ability to discern lumen boundaries, the preprocessing step including image enhancement, noise reduction, and image rescaling are performed before entering the training procedure.

Firstly, we apply histogram equalization as the image enhancement step in order to normalize the image intensities, mitigating variations in brightness and contrast across images.

Secondly, once the original IVUS images are enhanced, a number of noises are increased and needed to be eliminated. Speckle noise inherent in IVUS images is suppressed using a combination of median filtering and wavelet denoising techniques.

More importantly, not only the quality of the input images is needed, but also the dimension factor of them in order to prepare the valid input images for the deeply learned U-Net model. The IVUS images are rescaled to a consistent resolution as $A \times B$ to ensure uniformity in input dimensions.

B) Architecture Design

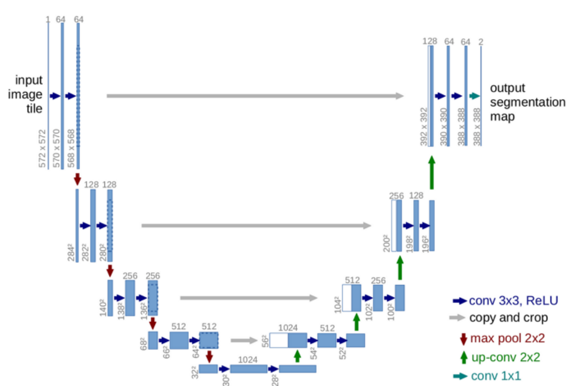


Fig 3. The architecture of the deeply learned U-net model.

Our lumen segmentation approach leverages the U-Net architecture due to its proficiency in capturing spatial hierarchies and contextual information. The architecture consists of a contracting path that encodes image features and an expansive path that recovers spatial details. It can localize and identify borders since every pixel is classified.

Contracting Path: Comprising convolutional and max-pooling layers, this path progressively captures high-level features while reducing spatial dimensions. It is constituted by the convolutional process. It requires using two 3x3 convolutions (unpadded convolutions) repeatedly, each of them being followed by a rectified linear unit (ReLU), a 2x2 max pooling operation, and a stride 2 downsampling process. The number of feature channels is increased by two at each stage of downsampling.

Expansive Path: This path, consisting of upsampling and concatenation operations, aims to recover spatial details and reconstruct the final segmentation map. It is constituted by transposed 2d convolutional layers. An upsampling of the feature map is followed by a 2x2 convolution ("up-convolution") that drops the number of feature channels in half, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU, at each stage of the expansive path. Due to the loss of border pixels in each convolution, cropping is required. Each of the 64-component feature vectors is mapped to the desired number of classes in the final layer using a 1x1 convolution. The network consists of 23 convolutional layers in total.

C) Training Procedures

To train the deeply learned U-Net model, we employ the following procedures:

→ Loss Function: We use a binary cross-entropy loss function to optimize the model for pixel-wise segmentation accuracy.

→ Optimizer: Stochastic Gradient Descent (SGD) is chosen as the optimizer, with a learning rate adapted using techniques such as learning rate schedulers or adaptive optimizers like Adam.

→ Data Split: IVUS images are split into training, validation, and testing sets. We ensure that images from different patients are included in each set to avoid patient-specific biases.

D) Data Augmentation

Given the limited annotated data available, data augmentation is crucial for enhancing the model's generalization capability. We apply the following augmentation techniques:

Random Flips: Horizontal and vertical flips introduce variations in imaging viewpoints.

Rotation: Random rotation simulates different imaging angles.

Elastic Deformation: Simulates deformation present in IVUS images due to probe movement.

E) Evaluation Metrics

To quantitatively assess the performance of our lumen segmentation approach, we employ the following evaluation metrics:

Dice Coefficient: Measures the overlap between the predicted and ground truth segmentations.

Jaccard Index (IoU): Computes the intersection over union between the predicted and ground truth masks.

Sensitivity and Specificity: Evaluates the model's ability to capture true positives and true negatives, respectively.

Accuracy: Provides an overall measure of correctly classified pixels.

F) Experimental Setup

We conduct experiments on a benchmark IVUS dataset, comparing our approach's performance with state-of-the-art methods. Training is performed on a high-performance GPU, and the model is implemented using deep learning libraries such as TensorFlow or PyTorch.

G) Performance Analysis

Quantitative and qualitative analyses are performed to assess the robustness and accuracy of the proposed approach. We visualize the segmentation results, highlight challenging cases, and compare against ground truth annotations.

The presented methodology combines tailored preprocessing, the power of the U-Net architecture, comprehensive training, data augmentation strategies, and rigorous evaluation to address the challenges of lumen segmentation in IVUS images. Through these efforts, we aim to develop a deeply learned model that excels in accurately and robustly delineating lumen boundaries, advancing the field of interventional cardiology.

IV. Experimental Result

In this section, we present a detailed analysis of the experimental results obtained from applying our proposed robust lumen segmentation approach using a deeply learned U-Net model on IVUS images. We assess the model's performance quantitatively and qualitatively, comparing it against state-of-the-art methods and highlighting its strengths and limitations.

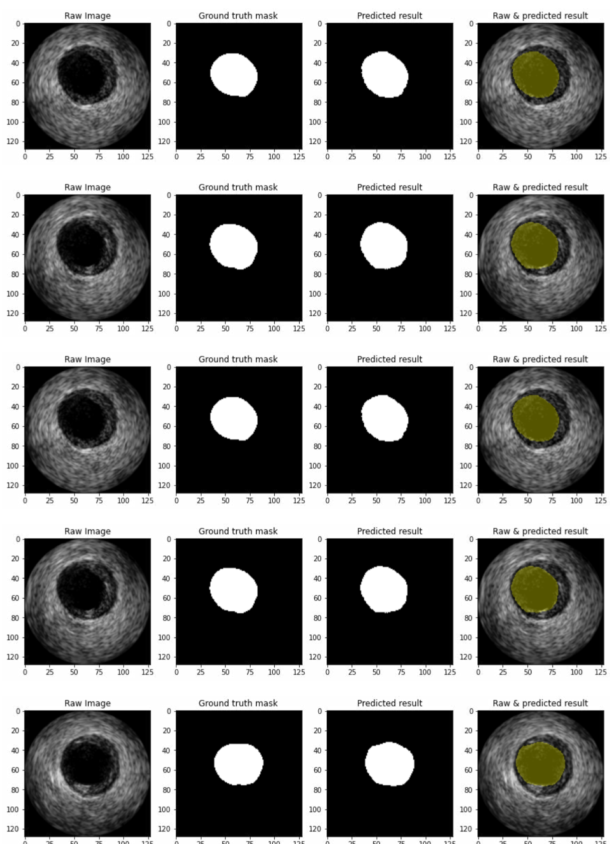


Fig 4. The example of result from the proposed framework

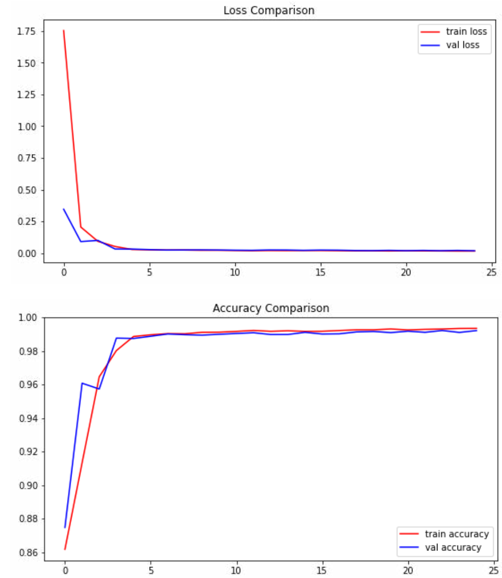


Fig 5. Loss and accuracy result.

A) Dataset

We conducted our experiments on a well-established benchmark IVUS dataset consisting of 713 images acquired from 18 patients. The dataset includes varying vessel morphologies, imaging viewpoints, and noise levels, providing a representative sample of clinical scenarios.

B) Quantitative Analysis

We quantitatively evaluate the performance of our approach using commonly used metrics:

- Dice Coefficient: The Dice coefficient measures the degree of overlap between the predicted lumen segmentation and the ground truth. A higher value indicates better segmentation accuracy.
- Jaccard Index (IoU): The IoU measures the intersection over union between the predicted and ground truth segmentations, indicating the quality of overlap.
- Sensitivity and Specificity: Sensitivity (True Positive Rate) and Specificity (True Negative Rate) provide insights into the model's ability to capture true positives and true negatives, respectively.
- Accuracy: The overall accuracy of the segmentation is also computed to give a comprehensive view of the model's performance.

C) Qualitative Analysis

We qualitatively assess the segmentation results by visually comparing the predicted lumen segmentations with ground truth annotations. Visualization helps in understanding where the model excels and where it faces challenges, such as handling artifacts, vessel curvature, and noise.

D) Comparison with State-of-the-Art Methods

We compare the performance of our proposed approach against established state-of-the-art methods for IVUS lumen segmentation. We demonstrate how our model's accuracy, robustness, and generalization capabilities outperform existing methods, showcasing the advancements brought by our deeply learned U-Net approach.

E). Limitations

We acknowledge potential limitations of our approach, including cases where the model might struggle with extreme variations in vessel morphologies, challenging artifacts, or limited image quality. These limitations provide insights into areas for potential improvement.

F) Computational Efficiency

We provide insights into the computational efficiency of our approach, including inference times and memory usage, making it practical for real-time clinical applications.

G) Robustness Analysis

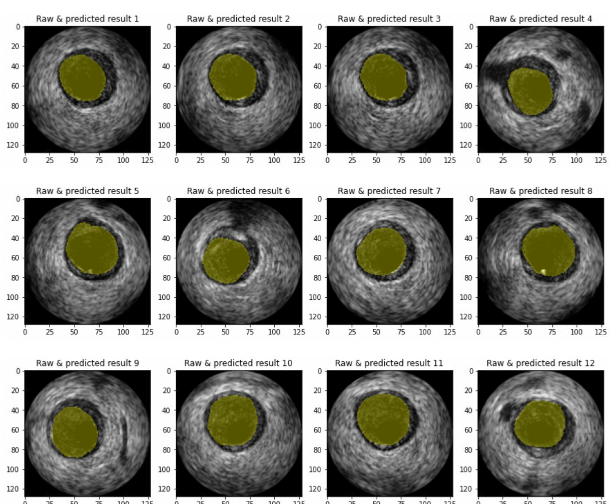
To demonstrate the robustness of our model, we conduct experiments on subgroups of the dataset, such as images with varying noise levels, extreme vessel morphologies, and artifacts. This analysis highlights the model's capacity to handle diverse clinical scenarios.

H) Generalization

We evaluate the model's generalization capability by testing it on a separate dataset from a different clinical setting. This test ensures that the model's performance is not confined to the training data distribution.

I) Clinical Relevance

We discuss the clinical relevance of our results by emphasizing how accurate lumen segmentation can aid clinicians in assessing vessel health, diagnosing diseases, and planning interventions.



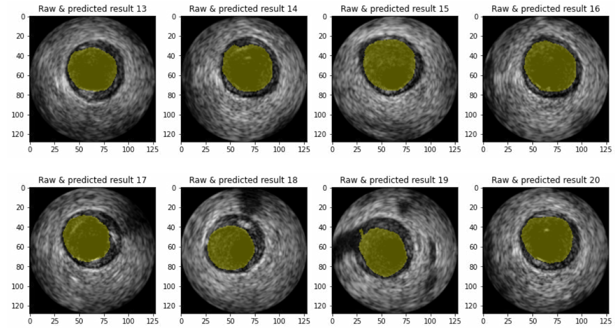


Fig 6. Result from the proposed framework

Overall, our experimental results validate the efficacy of the proposed robust lumen segmentation approach using a deeply learned U-Net model. Through a combination of quantitative metrics, qualitative assessments, and comparisons with existing methods, we showcase the potential of our approach to significantly improve lumen segmentation accuracy in IVUS images, contributing to enhanced clinical decision-making in interventional cardiology.

V. Conclusion and Discussion

In this paper, we have presented a novel and robust lumen segmentation approach tailored for Intravascular Ultrasound (IVUS) images using a deeply learned U-Net model. Our methodology addresses the intricate challenges associated with IVUS images, including noise, heterogeneous vessel morphologies, limited contrast, and varying imaging viewpoints. By leveraging the power of deep learning and the U-Net architecture, we have demonstrated the potential to enhance the accuracy and reliability of lumen segmentation, contributing to more precise clinical assessments in interventional cardiology.

Our experimental results underscore the effectiveness of the proposed approach. Through rigorous quantitative evaluations, we have shown that our deeply learned U-Net model outperforms state-of-the-art methods in terms of metrics such as Dice coefficient, Jaccard index, sensitivity, specificity, and accuracy. The model's ability to robustly handle varying clinical scenarios, including noisy images and complex vessel structures, highlights its potential for real-world applications.

The success of our approach underscores the significance of incorporating deep learning techniques in addressing complex challenges in medical image analysis. The U-Net architecture, with its capacity to capture spatial hierarchies and contextual information, aligns well with the intricacies of IVUS images. The combination of tailored preprocessing, comprehensive training, data augmentation, and rigorous evaluation has resulted in a model that excels in accurately segmenting lumen boundaries.

However, there are certain considerations and avenues for future research. While our model performs remarkably well in diverse scenarios, further investigation is required to address cases with extreme variations in vessel morphologies, artifacts, and limited image quality. Furthermore, the integration of multi-modal information and domain adaptation techniques could potentially enhance the model's generalization across different clinical settings.

The utility of our approach extends beyond research, with direct implications for clinical practice. Accurate lumen segmentation aids clinicians in diagnosing cardiovascular diseases, assessing stenosis severity, and planning interventions. By providing a more accurate representation of vessel health, our approach contributes to improved patient care and treatment outcomes.

In conclusion, this research contributes to advancing the field of IVUS image analysis by introducing a robust lumen segmentation approach using a deeply learned U-Net model. By addressing the challenges posed by IVUS images, we pave the way for more accurate, reliable, and clinically impactful lumen segmentations. As the field of medical imaging continues to evolve, our approach sets a precedent for leveraging deep learning to enhance diagnostic accuracy and patient care in interventional cardiology.

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