Interventional Catheter Segmentation for enhanced catheter manipulation in endovascular surgery and cardiology.

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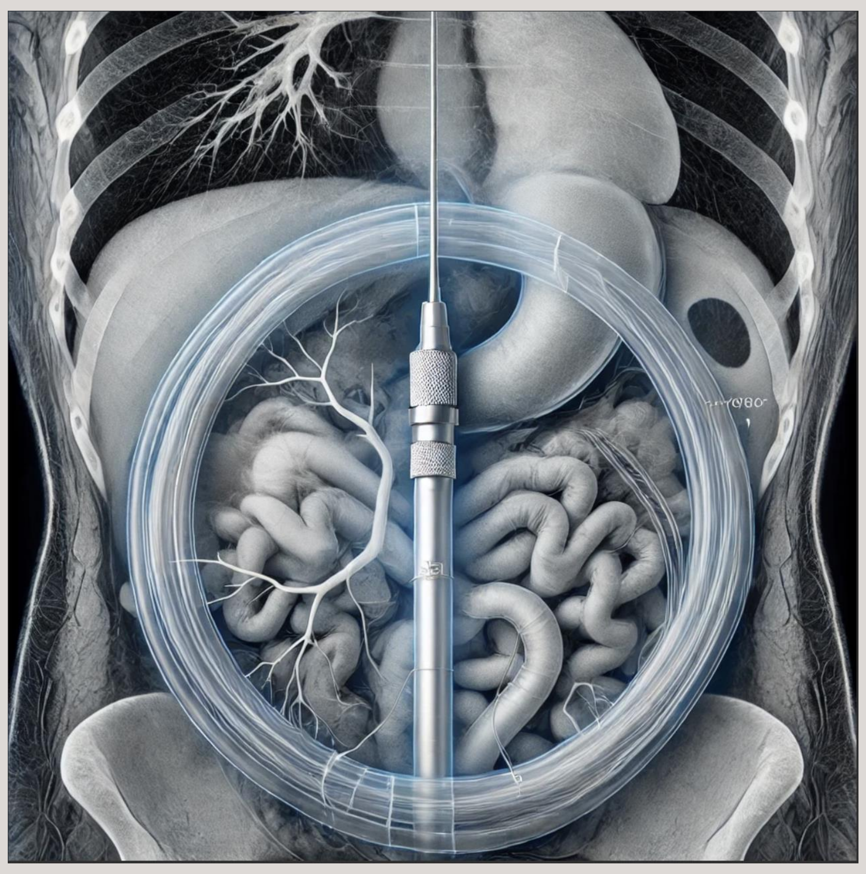
Introduction

- Catheter segmentation is a critical task in medical imaging, essential for guiding precise procedures and ensuring patient safety. Accurate segmentation enables better visualization and manipulation of catheters within complex anatomical environments.
- The task is particularly challenging due to the thin, tortuous nature of catheters, low contrast in imaging, and the presence of noise. These factors make it difficult for traditional segmentation methods to capture the fine details and continuity of these structures.
- This project compares the performance of the widely used UNet model [1] with the newly developed DSCNet model [2], aiming to improve segmentation accuracy and robustness in catheter segmentation tasks.



U-Net Model

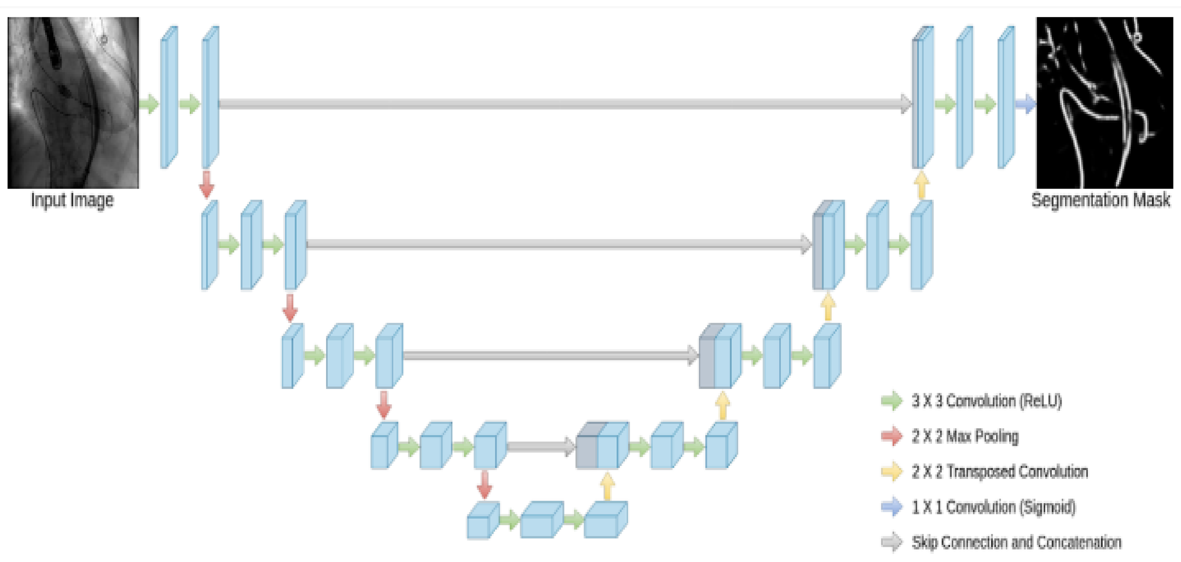
The U-Net model [1] is a well-known deep learning architecture designed for biomedical image segmentation.

Encoder-Decoder Structure:

- Features an encoder-decoder architecture with skip connections.
- Helps preserve spatial information while capturing fine details.

Importance of Dropout Layers:

- Prevents overfitting by randomly deactivating a fraction of neurons during training.
- Encourages the model to learn more robust features.
- Enhances the model's generalization ability, making it more effective in diverse medical imaging tasks.



DSCNet Model

The DSCNet model [2] is designed specifically to address the challenges of segmenting tubular structures like catheters in medical images, with innovations that enhance both accuracy and robustness.

Dynamic Snake Convolution (DSConv):

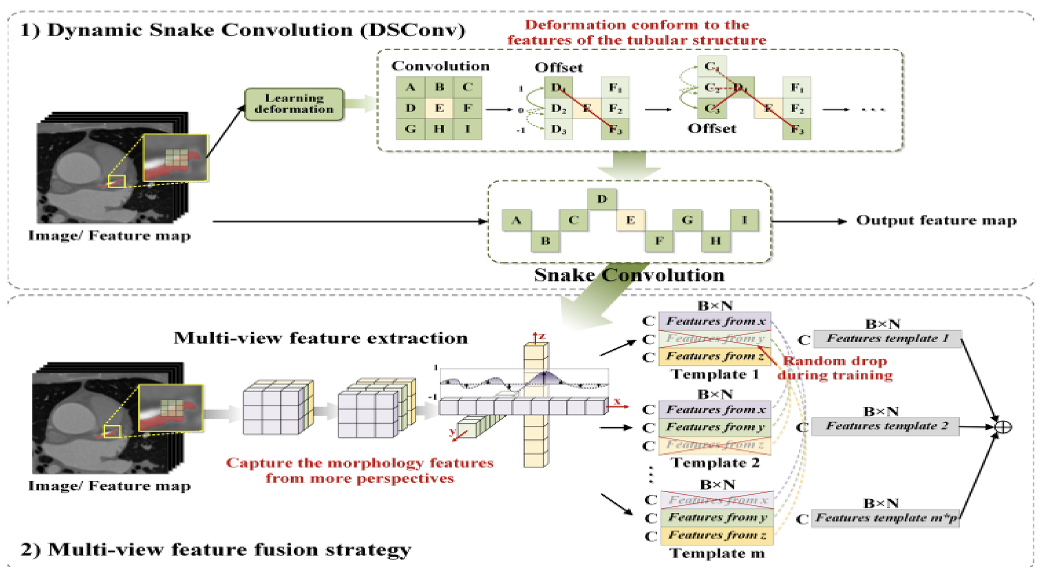
- Adapts convolutional filters to the shape of tubular structures, like catheters.
- Captures fine details in complex and tortuous anatomical regions.

Multi-View Feature Extraction:

- Captures morphological features from multiple angles.
- Enhances generalization across different anatomical structures.

Efficiency and Robustness:

- Outperforms traditional models like U-Net in accuracy and robustness, particularly in



Quantitative Results

Metrics	U-Net	DSCNet
IoU	0.7369	0.7679
Dice	0.7454	0.8677
RDice	0.7146	0.8468
clDice	0.9156	0.8930
AUC	0.9989	0.9353

Table 1: Segmentation Performance on Phantom

Metrics	U-Net	DSCNet
IoU	0.0976	0.1170
Dice	0.1458	0.2084
RDice	0.1458	0.2084
clDice	0.2641	0.2798
AUC	0.6610	0.5673

Table 2: Segmentation Performance on T1-T4 Datasets After Training on Phantom Dataset

Metrics	U-Net	DSCNet
IoU	0.3957	0.9355
Dice	0.3767	0.9666
RDice	0.3767	0.9666
clDice	0.7935	0.9264
AUC	0.9803	0.9832

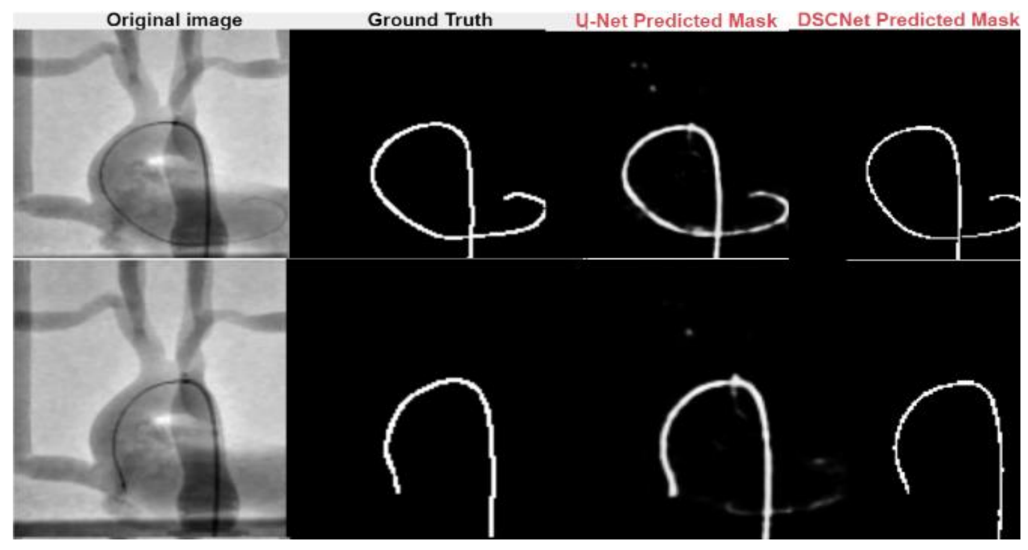
Table 3: Segmentation Performance on T1-T4 Datasets

Metrics	U-Net	DSCNet
IoU	0.0945	0.3183
Dice	0.1011	0.4721
RDice	0.1011	0.4721
clDice	0.2574	0.4925
AUC	0.8874	0.7444

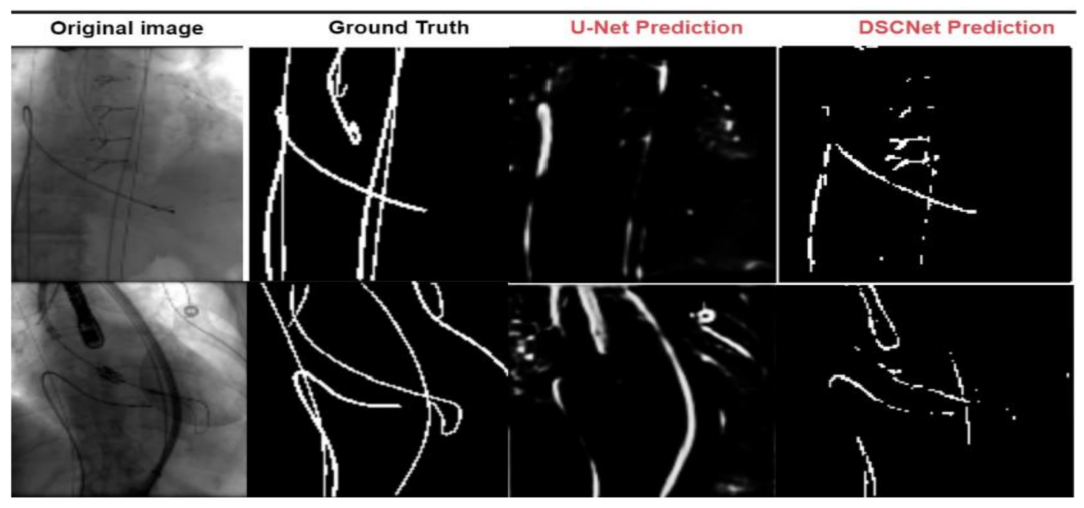
Table 4: Segmentation Performance on Phantom Dataset After Training on T1-T4 Datasets

Qualitative Results

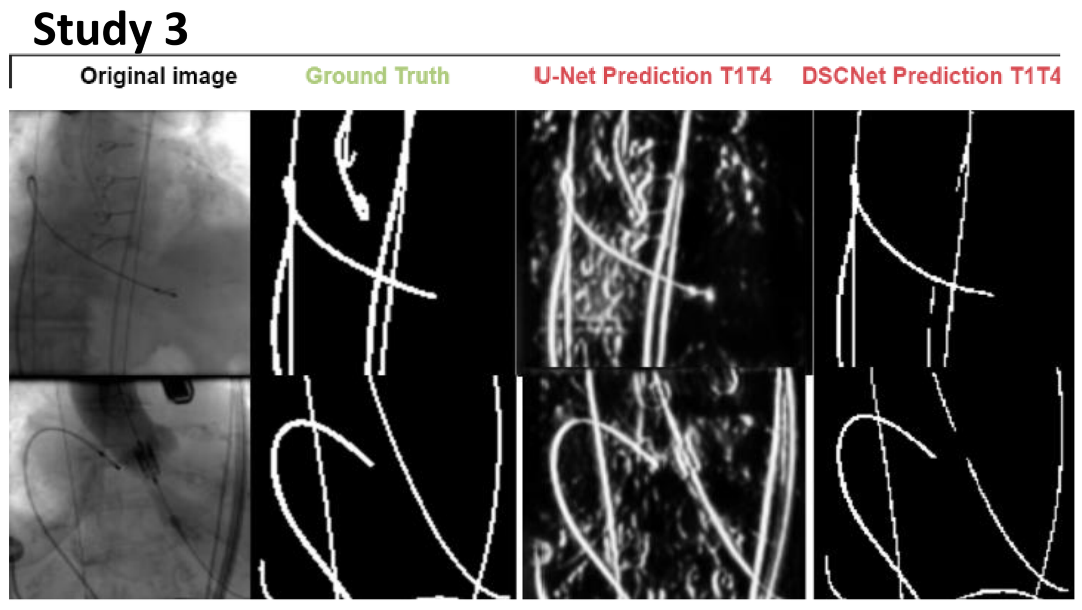
Study 1



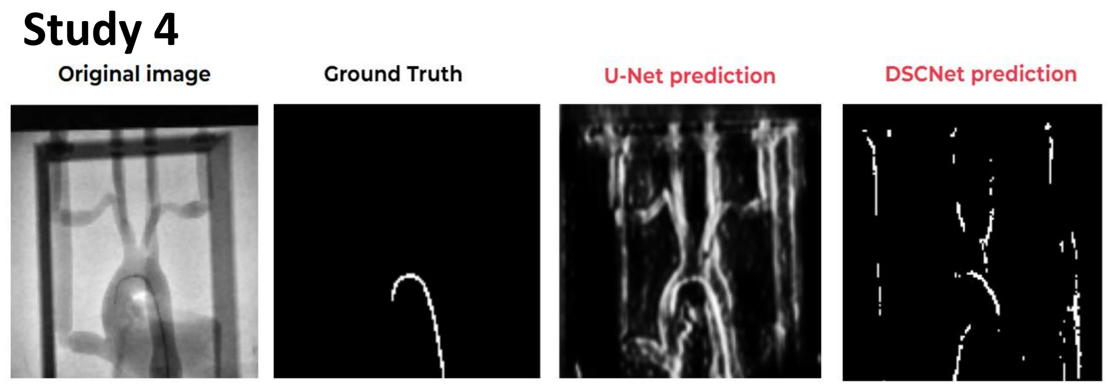
Study 2



Study 3



Study 4



Discussion

•DSCNet Effectively captures the intricate and complex structures of catheters, providing more accurate and continuous segmentation compared to UNet.

•Demonstrates strong adaptability and robustness, particularly in challenging imaging scenarios where catheter details are thin and tortuous.

•U-Net Performs well in standard cases, particularly with higher AUC scores, but struggles to maintain precision in more complex anatomical regions.

•Less effective in preserving the continuity and fine details of catheter structures.

•DSCNet proves to be a superior model for catheter segmentation, offering enhanced detail preservation and robustness, making it more reliable for complex medical. imaging tasks

Reference

[1] U-Net: Convolutional Networks for Biomedical Image Segmentation, arXiv: 1505.04597v1

[2] Dynamic Snake Convolution based on Topological Geometric Constraints for Tubular Structure Segmentation, arXiv: 2307.08388