Deep Learning for Vessel Segmentation in CTAs

Mayank Jain*[1] maj020@health.ucsd.edu
Albert Hisao[2,3] a3hsiao@health.ucsd.edu
Elsie Ross[1] e5ross@health.ucsd.edu
[1] *Department of Surgery, University of California, San Diego, California, USA*
[2] *Department of Radiology, University of California, San Diego, California, USA*
[3] *Halıcıoğlu Data Science Institute, University of California, San Diego, California, USA*

Editors: Under Review for MIDL 2025

Abstract

Accurate vessel segmentation from Computed Tomography Angiography (CTA) is crucial for clinical analysis, but manual methods are laborious, motivating the need for automated solutions. This work presents and evaluates a deep learning methodology for automated vessel segmentation across multiple anatomical regions in CTAs. Using a custom-developed labeling tool, we created a dataset of $\sim$ 54,000 patches from 51 CTAs. We employed a multitask learning Attention U-Net model, which combined vessel segmentation with body part classification, achieving an average classification F1 score of 0.866 and segmentation dice score of 0.87 across chest, abdomen, pelvis, and thigh with 5-fold cross-validation. Our findings offer insights into building effective automated vessel segmentation models, and we contribute our open-source labeling tool and training code to facilitate further research. Github: `https://github.com/Ross-Lab-UCSD/cta-vessel-segmentation`

Keywords: Image segmentation, Image labeling, Deep Learning, Medical imaging

1. Introduction

Computed Tomography Angiography (CTA) is a vital imaging modality providing vascular information essential for diagnosis and treatment planning across various conditions. Over the past decade, noninvasive imaging techniques like CTA have evolved into reliable alternatives to invasive angiography for assessing conditions such as peripheral arterial disease (PAD) (Leiner and Carr, 2019). Accurate segmentation of vascular structures within these scans is often a critical prerequisite for quantitative analysis, surgical guidance, and the development of automated diagnostic tools. However, manual delineation of complex vessel trees remains laborious, time-consuming, and subject to inter-observer variability, motivating the development of robust automated segmentation methods. While recent deep learning approaches segment vessels in specific regions like coronary arteries (Nannini et al., 2024) and (Wang et al., 2023), robust multi-region segmentation remains challenging.

This work investigates deep learning for multi-region vessel segmentation using an Attention U-Net architecture. We utilize a dataset derived from 51 clinical CTAs covering multiple body parts (chest, abdomen, pelvis, thigh, below knee), annotated using our custom-developed, semi-automated labeling tool. We evaluate and compare two distinct training strategies: (1) training separate Attention U-Net models specifically on data from individual body parts, versus (2) training a single multi-task Attention U-Net model on the combined dataset from all regions. This multi-task model is designed to perform vessel segmentation while concurrently classifying the body part shown in the input slice.

* Corresponding author

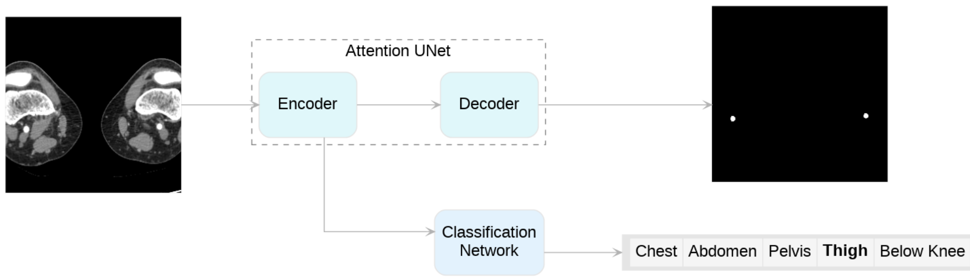

Figure 1: Multitask learning Attention UNet Model

2. Methods

2.1. Dataset

The dataset for this study was derived from 51 anonymized CTA scans collected at our institution. We generated ground truth segmentations using a custom-developed, open-source, interactive tool that facilitates rapid annotation (approx. 1500 slices/minute) via user-initialized seed points, semi-automated region growing/tracking, and manual refinement options. The labeled volumes were then processed to extract 2D image-mask pairs. A total of 54,585 patches of size 256x256 pixels were extracted across various anatomical regions including the chest, abdomen, pelvis, thigh and below knee. For model training and evaluation, a 5-fold cross-validation strategy was employed, splitting the data based on patient ID to prevent data leakage. Within each fold, this resulted in an approximate split of $\sim$ 43,000 patches for training and $\sim$ 11,000 patches for validation. The distribution of samples across the different body parts is illustrated in Table 1.

Table 1: Distribution of number of samples per body part

Body Part	Training	Validation
Chest	6,450	1,612
Abdomen	5,251	1,312
Pelvis	9,620	2,405
Thigh	13,736	3,434
Below Knee	8,612	2,153
Total	**43,669**	**10,916**

2.2. Deep learning segmentation model

For vessel segmentation, we employed Attention UNet (Oktay et al., 2018), selected for its implementation simplicity and effectiveness in medical image segmentation. The specific architecture accepts 256x256 single-channel input patches and outputs a corresponding single-channel segmentation map. We compared two modeling approaches to assess the utility of shared representations: 1) models trained specifically on data from individual body parts, 2) a multi-task learning (MTL) Attention UNet model trained on all data. The MTL variant incorporates an additional classification head, applied to the encoder's bottleneck features to concurrently predict the body part class associated with the input slice. Further implementation details and hyperparameters can be found in the code repository.

3. Results

We evaluated the performance of two distinct training strategies: 1) body-part specific Attention U-Nets, referred to as Single-Part, and 2) Multi-task learning (MTL) Attention U-Net, using the 5-fold cross-validation. Segmentation performance was assessed using the Dice similarity coefficient (Dice Score), while the classification performance of the auxiliary task in the MTL model was evaluated using the F1 score.

Table 2: Dice Scores for Segmentation and F1 Score for Body Part Classification

Body Part	**Segmentation: Dice Score**		**Classification: F1 Score**
	Single-Part	**MTL**	**MTL**
Chest	0.9582	0.9516	0.91
Abdomen	0.8417	0.8490	0.79
Pelvis	0.8193	0.8216	0.81
Thigh	0.8669	0.8501	0.87
Below Knee	0.6483	0.5639	0.95

4. Conclusion and Discussion

The multi-task learning (MTL) Attention U-Net achieved segmentation dice scores comparable to specialized single-part models for the chest, abdomen, pelvis, and thigh, demonstrating effective generalization and learning of shared vascular features across diverse anatomies without needing region-specific models. Notably, the Single-Part model yielded superior results for the Below Knee region, potentially due to the unique challenges posed by the smaller vessels in this area, suggesting additional data might be needed for this region.

Crucially, the MTL model also demonstrated high efficacy in its auxiliary task, achieving high F1 scores for body part classification. This secondary capability is valuable beyond the segmentation task itself; it offers a practical mechanism for automatically categorizing and organizing large, heterogeneous datasets. This can significantly streamline the process of curating and expanding datasets for future model development.

In conclusion, the multi-task learning approach offers an efficient strategy for generalized vessel segmentation in multi-region CTAs, adding valuable data categorization capabilities. Our open-source contributions aim to facilitate further research towards robust, automated vascular analysis tools.

Acknowledgments

We thank Doris Duke Foundation for research funding.

References

Tim Leiner and James C. Carr. *Noninvasive Angiography of Peripheral Arteries*, page 223–238. Springer International Publishing, 2019. ISBN 9783030111496. doi: 10.1007/978-3-030-11149-6_20. URL http://dx.doi.org/10.1007/978-3-030-11149-6_20.

Guido Nannini, Simone Saitta, Andrea Baggiano, Riccardo Maragna, Saima Mushtaq, Gianluca Pontone, and Alberto Redaelli. A fully automated deep learning approach for coronary artery segmentation and comprehensive characterization. *APL Bioengineering*, 8(1), January 2024. ISSN 2473-2877. doi: 10.1063/5.0181281. URL http://dx.doi.org/10.1063/5.0181281.

Ozan Oktay, Jo Schlemper, Loic Le Folgoc, Matthew Lee, Mattias Heinrich, Kazunari Misawa, Kensaku Mori, Steven McDonagh, Nils Y Hammerla, Bernhard Kainz, Ben Glocker, and Daniel Rueckert. Attention u-net: Learning where to look for the pancreas, 2018. URL https://arxiv.org/abs/1804.03999.

Qianjin Wang, Lisheng Xu, Lu Wang, Xiaofan Yang, Yu Sun, Benqiang Yang, and Stephen E. Greenwald. Automatic coronary artery segmentation of ccta images using unet with a local contextual transformer. *Frontiers in Physiology*, 14, August 2023. ISSN 1664-042X. doi: 10.3389/fphys.2023.1138257. URL http://dx.doi.org/10.3389/fphys.2023.1138257.