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Automated 3D kidney blood vessel segmentation using deep learning techniques

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Introduction

The human vascular system, with its complex network of blood vessels varying in size and intricate branching patterns, presents substantial challenges for accurate and effective segmentation. Recent advancements in computational models and imaging techniques are leading in a new era of possibilities in medical imaging. This research aims to use cutting-edge deep learning approaches and sophisticated segmentation frameworks to kidney imaging, to address these challenges.

- **Research Objectives:**
  1. Develop Advanced Segmentation Models: Aim to create and refine machine learning models capable of producing highly accurate vascular segmentation from high-resolution 3D kidney imaging data.
  2. Enhance Understanding of Vascular Structures: Use the detailed images provided to deepen the understanding of kidney vascular architecture and its variations.
  3. Optimize Performance Across Varied Resolutions: Ensure that the segmentation models perform consistently well across different resolutions and conditions as presented in the diverse dataset.
  4. Contribute to Medical Imaging Research: Provide insights and methodologies that could potentially be applied to other areas of medical imaging, enhancing diagnostic and research capabilities in the field of radiology.

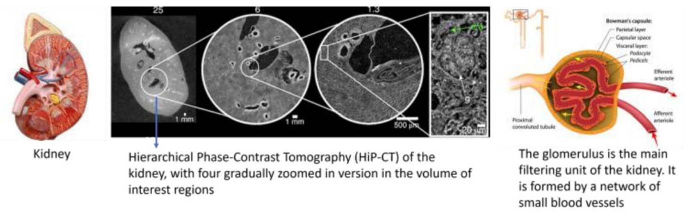

Fig 1: HPT-CT imaging of the kidney for blood vessel segmentation (adapted from [2])

Methodology

Python Libraries:

- Segmentation-models-Pytorch
- Torchvision
- Transformers
- Scikit-image
- OpenCV

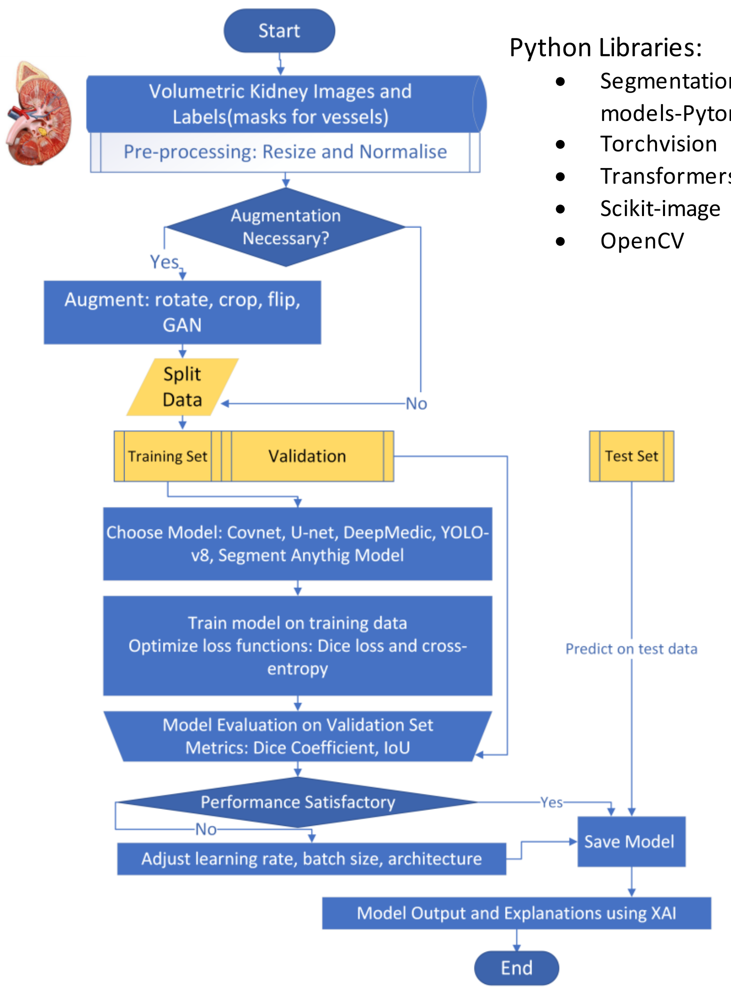

Figure 2: Implementation stages of the blood vessel segmentation model

Dataset Overview

The dataset[1] for this research consists of high-resolution 3D images and segmentation masks of human kidneys, obtained through Hierarchical Phase-Contrast Tomography (HiP-CT). HiP-CT captures detailed 3D data from ex vivo organs with resolutions ranging from 1.4 micrometers to 50 micrometers. The primary task involves creating accurate segmentation masks for the kidney datasets in the test set, which includes various resolutions and segmentation details.

Data Subsets /Resolution/no. of images	Purpose
Kidney_1_dense: Complete right kidney imaged at 50 µm, Densely segmented, covering the entire 3D arterial vascular tree down to two generations from the glomeruli. 2279 Slices	This subset will be used for capturing detailed internal structures due to high coherence and brightness.
Kidney_1_voi: A high-resolution subset of kidney_1 at 5.2 µm with specific volume of interest (voi). 1397 Slices	Showcases the capabilities of HiP-CT at higher resolutions and to assist in developing algorithms that can handle detailed microvascular structures.
Kidney_2: Entire kiney from another donor imaged at 50 µm, sparsely segmented at approximately 65%, focusing on major vascular structures without capturing all minute details, 2217 Slices	Offers a challenge in interpolating incomplete data and tests the model's ability to generalize from partial information.
Kidney_3_dense: A portion of Kidney 3 at 50.16 µm, 500 Slices, densely segmented	This subset provides a comprehensive data for a segment of the kidney which aids in detailed analysis and model training.
Kidney_3_sparse: Complements the dense dataset by providing the remaining segmentation masks for kidney_3. 1035	This subset challenges the ability to maintain continuity and accuracy in vascular mapping with less comprehensive data coverage.

Model Evaluation and Discussion

Model Evaluation Matrices:

To evaluate semantic segmentation several different metrics are used in the literature. In this research, we used the Dice score, Mean Intersection over Union (MIoU) to evaluate the model performance.

- **Dice Score** measures the similarity between the predicted and ground truth segmentation, indicating the accuracy of segmentation for various images.
  - $Dice = \frac{2\times|A\cap B|}{|A|+|B|}$

  where A and B are the prediction and ground truth segmentations, respectively.
- **Mean Intersection over Union (mIoU)** computes the average IoU across all images, measuring the overlap between the predicted and ground truth masks to assess overall segmentation accuracy.
  - $\mathrm{IoU}(A, B) = \frac{A\cap B}{A\cup B}$

Discussion:

- This research is still in its developmental stage. However, our initial exploration is showing promising results with multiple models such as U-net and Covnet. These models showed high IOU (>70%) showing the models effectiveness in delineating precise boundaries, even in the dense and sparse subsets of the kidney data.
- We also noticed the segmentation of the human kidney's vascular structures poses significant challenges due to the complex and varying nature of blood vessels. We noticed discrepancies in segmentation performance across different resolutions. Hence, we are currently refining the algorithms and exploring further methodologies to better handle the challenges posed by sparse data and to enhance their applicability to real-world clinical settings.

References:

1. Data Source: https://www.kaggle.com/competitions/blood-vessel-segmentation/data
2. Yagis, E., Aslani, S., Jain, Y., Zhou, Y., Rahmani, S., Brunet, J., Bellier, A., Werlein, C., Ackermann, M., Jonigk, D., Tafforeau, P., Lee, P.D. & Walsh, C., 2023. Deep Learning for Vascular Segmentation and Applications in Phase Contrast Tomography Imaging. *ArXiv*. DOI: 10.48550/arXiv.2311.13319.
3. Sweeney, P., Hacker, L., Lefebvre, T.L., Brown, E.L., Gröhl, J. and Bohndiek, S., 2023. Segmentation of 3D blood vessel networks using unsupervised deep learning. bioRxiv. DOI: 10.1101/2023.04.30.538453.
4. Liu, P., Huang, G., Jing, J., Bian, S., Cheng, L., Lu, X.Y., Rao, C., Liu, Y., Hua, Y., Wang, Y. and He, K., 2023. An Energy Matching Vessel Segmentation Framework in 3D Medical Images. IEEE Transactions on Medical Imaging. DOI: 10.1109/TMI.2023.3339204.