Renal Artery Image Segmentation and 3D Modeling of Abdominal Aortic Vessels

Note: This document is a technical summary of the author's Capstone Project Report, which is available in Chinese. This summary focuses on the key methodologies, innovative contributions, and quantitative results.
Full report (in Chinese) and code: github.com/YuHo0

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1. Executive Summary

Objective: To reduce the risk of rupture in Abdominal Aortic Aneurysms (AAA) and assist surgeons in preoperative planning for Endovascular Aneurysm Repair (EVAR).

The Problem: Current preoperative assessment relies heavily on manual interpretation of CT scans to determine stent placement zones. This process is time-consuming, prone to human visual fatigue, and carries a risk of misjudging the critical junction between the aorta and renal arteries.

Key Breakthrough: I achieved a **+21.8% improvement** in kidney detection accuracy (mAP: **99.1%** with Split Training) and significantly enhanced segmentation performance (Mean IoU: **0.932**), demonstrating state-of-the-art results on clinical data.

The Solution: I developed an integrated automated system that processes raw DICOM CT slices. By combining object detection (YOLO) for anatomical localization and semantic segmentation (U-Net) for vessel extraction, the system successfully reconstructs high-fidelity **3D STL models** of the abdominal aorta, providing surgeons with a precise 3D visualization of the vascular structure.

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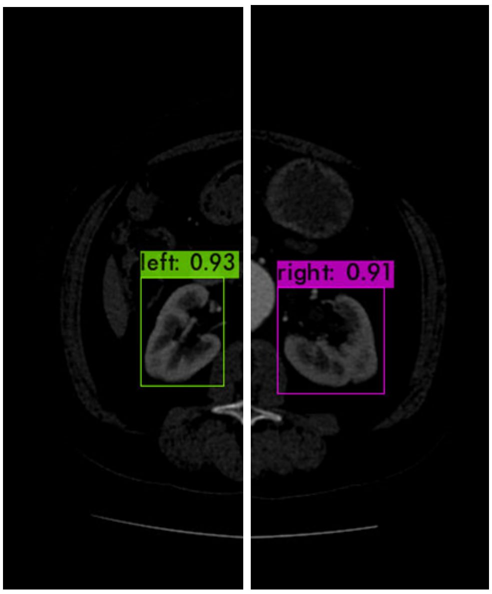
2. Visual Demonstration

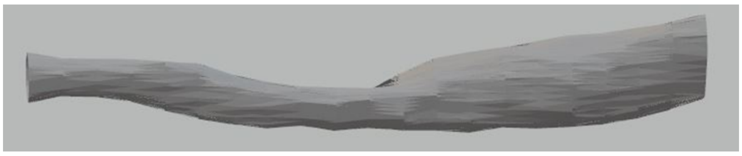
- *Intelligent Localization.* The system automatically detects the left and right kidneys (Green/Pink bounding boxes) to define the surgical ROI.



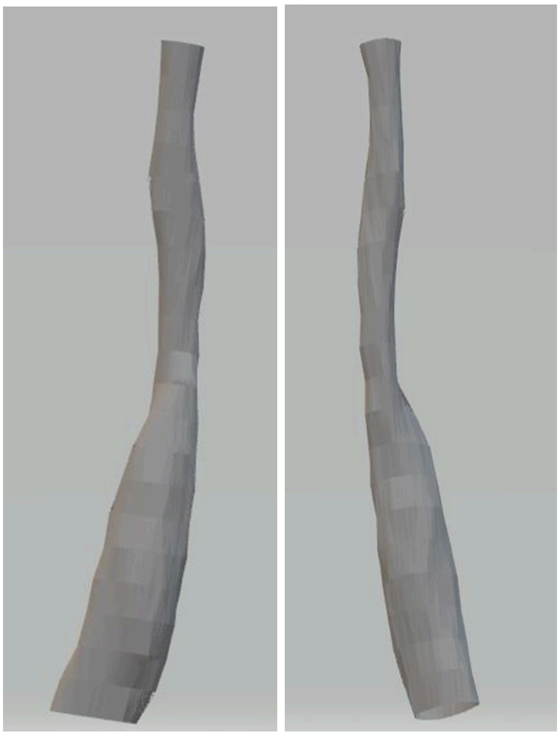
- *Precise Segmentation.* The U-Net model accurately delineates the aorta-renal connection points (white contours) from the background.

Original Image/ Vascular Contour Labeled Mask/ Original Image and Mask Overlay
Schematic Diagram of the Aorta-Renal Connection Vascular Contour Labeled Mask

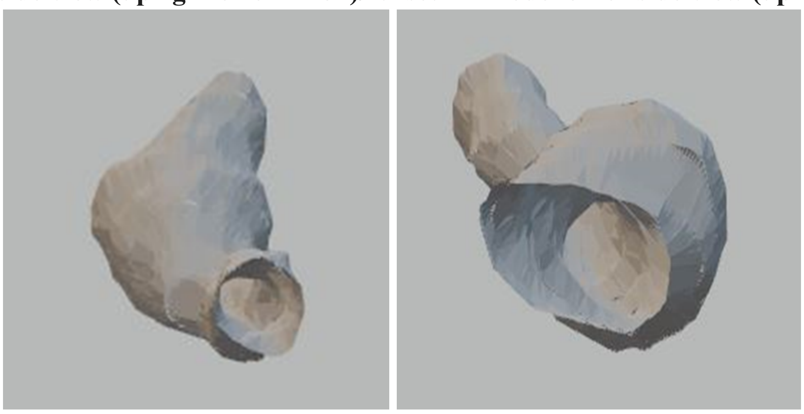
- *3D Reconstruction Results.* The final generated 3D STL models viewed from multiple angles, showing the hollow vascular structure essential for stent planning.



Vascular model side view (horizontal orientation)



Vascular model side view (upright orientation)/ Vascular model other side view (upright orientation)



Vascular model superior view/ Vascular model inferior view

3. Technical Methodology & Pipeline

The system utilizes a multi-stage "coarse-to-fine" approach to filter irrelevant data and focus computational resources on the Region of Interest (ROI).

- **Phase 1: Image Preprocessing**
  - Converted DICOM files to BMP format with specific window settings (WL: 300, WW: 600) to highlight vascular structures.
  - Applied **Gamma Correction (gamma=0.1)** and **Otsu's Binarization** to significantly enhance contrast between the aorta and soft tissues, separating the trunk contour from the background.
- **Phase 2: Intelligent ROI Localization (YOLOv4/v7)**
  - **Spine Detection:** Utilized YOLO models to identify thoracic (T12) and lumbar (L3) vertebrae, establishing a baseline anatomical range for the aneurysm.
  - **Kidney Detection (Split-Training Strategy):** To address anatomical asymmetry, I implemented a split-training strategy, training separate models for left and right kidneys. This optimization drastically improved detection accuracy compared to joint training.
- **Phase 3: Vessel Segmentation (U-Net)**
  - Deployed a U-Net architecture to perform pixel-level segmentation of the aorta and the critical aorta-renal connection points.
  - The model generates precise binary masks of the blood flow lumen, filtering out non-vascular tissues.
- **Phase 4: 3D Reconstruction**
  - Processed the segmented 2D masks using morphological erosion to simulate hollow vessel walls.
  - Constructed a **Triangular Mesh (STL format)** by stacking voxel points along the Z-axis, allowing for 3D rotation and depth analysis in surgical software.

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4. Key Results & Performance

The proposed method demonstrated state-of-the-art performance on clinical datasets provided by China Medical University Hospital.

Quantitative Benchmarks:

Metric	**Baseline / Previous Method**	**My Optimized Method**	**Improvement**
Kidney Detection (mAP)	77.3% (Joint Training)	**99.1%** (Split Training - YOLOv7)	**+21.8%**

Segmentation (Mean IoU)	0.759 (Raw Images)	**0.932** (Preprocessed)	**+17.3%**
Segmentation Precision	84.2%	**96.7%**	**+12.5%**

5. Clinical Impact & Future Scope

- **Surgical Safety:** Ensures stents are placed below the renal arteries to prevent renal failure, a key requirement for EVAR success.
- **Workflow Efficiency:** Automates the slice selection process, reducing the time radiologists spend manually scrolling through hundreds of CT slices.
- **Future Application:** The generated STL models are ready for Computational Fluid Dynamics (CFD) analysis to simulate blood flow pressure and wall stress.